ROBUST SENSITIVITY ANALYSIS FOR THE JOINT IMPROVISED EXPLOSIVE DEVICE DEFEAT ORGANIZATION (JIEDDO) PROPOSAL SELECTION MODEL

THESIS

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AFIT/GOR/ENS/09-17

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THESIS

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Operations Research

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March 2009

AFIT/GOR/ENS/09-17

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Abstract

Throughout Operations Iraqi Freedom and Enduring Freedom, the Department of Defense (DoD) faced challenges not experienced in our previous military operations. The enemy's unwavering dedication to the use of improvised explosive devices (IEDs) against the coalition forces continues to challenge the day-to-day operations of the current war. The *Joint Improvised Explosive Device Defeat Organization's (JIEDDO)* proposal solicitation process enables military and non-military organizations to request funding for the development of Counter-Improvised Explosive Device (C-IED) projects.

Decision Analysis (DA) methodology serves as a tool to assist the decision maker (DM) in making an informed decision. This research applies Value Focused Thinking (VFT), a specific methodology within DA, to the JIEDDO proposal selection process in order to assist DMs in filtering out proposals that do not meet desired C-IED objectives.

This research evaluated the validity of the previously developed JIEDDO Proposal Value model to address the following questions: *Does the value model adequately reflect JIEDDO's decision process; and secondly, given the dynamic environment of the current war, how confident can we be in the model's ability to continually and effectively screen proposals based JIEDDO's current values?* The author utilizes multivariate techniques to investigate JIEDDO's ability to make consistent decisions within their proposal evaluation process. Once it has been determined that the model effectively screens proposals, it is possible to proceed with the second question. By consolidating and applying n-way sensitivity analysis techniques the author proposes a consistent sensitivity analysis image profiling technique.

To Mom and Dad

Acknowledgments

I would like to express my sincere gratitude to my faculty advisor, Dr. Ken Bauer for his persistent direction and enthusiasm throughout this research process. His invested interest in helping me to make new contributions was encouraging and made my experience enjoyable. My research would not be complete without the support of my committee members, Col. Dan Zalewski and Maj. Shane Knighton. Col. Zalewski helped significantly in the sharing of ideas between JIEDDO and me. This communication link was critical in ensuring that we were on track with delivering a desired product. I am grateful for his time and contributions throughout this research journey. Additionally, I would like to acknowledge Maj. Knighton for his guidance and recommendations as we worked to build bridges between the fields of Decision Analysis and Multivariate Analysis in order to meet our research objectives. Lastly, I would like to thank my thesis editor, Ms. Trisha Gargaro, for her willingness to read and provide feedback on the writing style of this document.

Christina J. Willy

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ROBUST SENSITIVITY ANALYSIS FOR THE JOINT IMPROVISED EXPLOSIVE DEVICE DEFEAT ORGANIZATION (JIEDDO) PROPOSAL SELECTION MODEL

I. Introduction

Commanders make decisions that require conscientious examination of the options under their control. They rely on decision analysts to utilize the tools and techniques thereof to aid their decision making process. The recently proposed Joint Improvised Explosive Device Defeat Organization (JIEDDO) value model is capable of serving as a filtering tool for evaluating Counter-Improvised Explosive Device (C-IED) proposals to become fully funded initiatives. Although JIEDDO recognizes that using a tool to track a proposal's positive and negative characteristics and provide justifiable feedback to the applicant is useful, they have expressed a desire for more confidence in the model's ability to reflect adequately the decision at hand. Much of their willingness to embrace the model lies in the analyst's ability to demonstrate that it is a valid representation of their decision process. In order to meet their request, it is necessary to show that the model does in fact reflect the proposal evaluation process and that it will continue to do so as the organization evaluates future proposals. A great deal of the evaluation relies on the robustness of the weighted values that are the basis for evaluating a given proposal.

The architects of the original JIEDDO value model recognized the importance of conducting sensitivity analysis on the weights and provided substantial one-way and two-way sensitivity analysis to the decision problem. However, their post model analysis did not include model weight adjustments for three or more values simultaneously. This thesis applies multivariate techniques to conduct n-way sensitivity analysis in order to aide decision makers from JIEDDO and other organizations to assert confidently their assessment of alternatives. With this knowledge, they will thereby make a decision fully grounded in the values that encapsulate the issues under consideration.

I.A. Background

JIEDDO

From October 2003 to August 2008 the total number of reported U.S. fatalities in Iraq attributed to detonated IEDs summed to 1717 people (Iraq Collation Causualty Count). According to the Congressional Research Service, IEDs account for 60 percent of all U.S. “combat casualties both killed and wounded” in Iraq and 50 percent in Afghanistan (United States Government Accountability Office , 2008). In the first three years of the war, the Secretary of Defense recognized a need for a well-established and organized C-IED organization.

In February 2006, the Department of Defense (DoD) organized the joint C-IED efforts of the Joint Improvised Explosive Devise Defeat Task Force by establishing the Joint Improvised Explosive Device Defeat Organization (JIEDDO: About Us). JIEDDO’s current mission is “to lead, advocate and coordinate all DoD actions in support of Combatant Commanders’ and their respective Joint Task Forces’ efforts to defeat improvised explosive devices (IEDs) as weapons of strategic influence” (JIEDDO: About Us).

In order to remedy the current IED problem, JIEDDO solicits support from military and civilian communities. JIEDDO identifies C-IED proposals that meet the needs of our current warfighter, ensures the contribution of appropriate funding to these initiatives, and more importantly delivers an effective product to implement in the field.

JIEDDO's current proposal solicitation policy requires interested parties to submit their C-IED proposals to the Broad Area Announcement Information Delivery System (BIDS) (JIEDDO: About Us). BIDS communicates to the public JIEDDO's current interests in the way of C-IED capabilities and receives proposals for potential future C-IED initiatives. Traditionally, when a proposal is submitted to JIEDDO for consideration, it undergoes an extensive evaluation process that involves a panel of 14-16 subject matter experts (SMEs) who assess a group of proposals over a three-day time period (Mauldin, 2008). The team of evaluators is unavailable to conduct the duties of their day-to-day job during this time period. The panel reviews proposals based on the characteristics (or variables) that each proposal claims it will achieve. Upon completion, the panel recommends to the JIEDDO Director the rejection or acceptance of the proposal (Mauldin, 2008). Upon hearing these recommendations, the Director reviews programmatic and resource implications for selecting the proposed C-IED initiatives and provides the stamp of approval for the proposal to enter the first stage of the acquisition process (Mauldin, 2008).

House Armed Service Committee Oversight & Investigation of JIEDDO

JIEDDO's ability to carry out its C-IED mission heavily relies on having the fiscal funds to do so. Congress has recognized this need and has been monetarily accommodating. In fiscal year 2007 alone, Congress provided approximately $4.35 billion to JIEDDO (United States Government Accountability Office , 2008). The influx of monetary resources is expected to continue pending JIEDDO's ability to demonstrate its productivity and efficiency within the DoD.

JIEDDO's large congressionally appropriated budget and delicate mission, however, have made it the Government Accountability Office's (GAO) target for investigation. Over the past two years, the GAO conducted audits to evaluate JIEDDO's ability to effectively and appropriately carry out the C-IED mission. In their initial report in March 2007, the GAO investigated JIEDDO's "management and operations" ability (United States Government Accountability Office , 2008). JIEDDO was criticized for an apparent "lack of a strategic plan and the resulting effects on the development of its financial and human capital management programs" (United States Government Accountability Office , 2008). Approximately one year after an initial review, in 2008, the GAO re-attacked with focused efforts on JIEDDO's financial management process and the organization's ability to "identify, record, track, and report" on all employees to include contractors (United States Government Accountability Office , 2008).

In spite of all the scrutiny, JIEDDO remains confident that they are winning the C-IED fight. Providing detailed proof of this statement, however, poses great challenges. In addition to the GAO, the public at large seeks substantial evidence that JIEDDO is making a substantial positive difference in the current war.

Decision Analysis

Decision Analysis (DA) is a field within Operations Research that helps the community at large by aiding decision makers to make appropriate and informed decisions. More specifically, DA is used as a means to aid the decision maker (DM) in selecting the "best" alternative for a given decision problem. For JIEDDO, the conscientious evaluation of C-IED proposals, though important, requires careful examination by numerous involved parties to ensure the selected proposals are qualified.

A decision analysis model provides a consistent systematic framework for proposal evaluation and decision justification (Dawley, Marentette, & Long, 2008).

To construct a model that adequately encapsulates the decision problem, it is crucial that the analyst works with the appropriate DM to identify all of the values for the decision at hand. After identifying the values, it is possible to determine the measures by which the values will be evaluated. The analyst works with the DM to determine the weights for each of the identified values. The weights reflect the DM's preferences within the decision problem.

For the JIEDDO proposal evaluation process, utilizing a decision model that encapsulates the appropriate DM's values as a decision making tool serves a dual purpose. First, it serves as a filtering tool that allows senior leaders, such as those serving on the proposal evaluation panel, to concentrate their efforts on examining proposals that have the greatest potential for meeting the C-IED mission requirement and implementing them appropriately. Second, it exploits DA techniques to provide a "defensible and repeatable framework" to aid the proposal screening process (Dawley, Marentette, & Long, 2008).

Sensitivity Analysis

A value model produces a score for each alternative using an additive value function calculation that is the sum of the weighted values themselves. From these scores, the DM identifies the best alternative, that which possesses characteristics that they value most. Prior to taking action, however, it is necessary to evaluate the sensitivity of the alternatives to weight change variations.

The weights reflect the DM's preferences. Consequently, they are subjective. It is important to investigate how scores produced using the additive value function are affected by weight changes if the DM's preferences are different than those originally solicited. Thus, if the DM is slightly off in their assessment of the weights, how confident can we be in selecting a particular alternative? Sensitivity analysis allows the decision maker to view how perturbing the weight for a particular value affects the decision outcome.

Traditionally, analysts conduct one-way sensitivity analysis to identify single-handedly which value affects the decision problem most (Skinner, 1999). Similarly, two-way sensitivity analysis allows for the alteration of two different weights simultaneously and observing changes in the decision outcome. In most cases, one-way and two-way sensitivity analysis provide a "screening" process for identifying which weights have the greatest potential to affect the decision problem (Bauer, Parnell, & Meyers, 1999). Although the effects of altering one or two weights are convenient analysis endeavors, the majority of real world situations have uncertainty in more than two weights. From this, we are faced with the following questions: What are the consequences of altering three, four, five, or n weights simultaneously? Will altering each of the weights by even a small amount relative to its original weight completely restructure the ranking of alternatives themselves (Bauer, Parnell, & Meyers, 1999)? Addressing such questions will allow analysts to gain insight into the validity and robustness of value models like the proposed JIEDDO Proposal Value Model. Once we have adequately addressed these issues, it is possible to determine whether further utilization of such a value model is appropriate.

I.B. Problem Statement

For JIEDDO the consequences of suboptimally allocating funds as a result of inconsistent decisions has the potential of leaving the warfighter ill equipped to meet mission requirements and defend against IED attacks. Additionally, inconsistency within the proposal evaluation process could be disastrous for an organization that fails to adequately justify their reasons for making important decisions. It is clear that these weaknesses are at the front of the GAO's motivation for investigating JIEDDO's current lines of operations, among which include proposal evaluation for selection or rejection in the earliest stages of the acquisition process.

The importance of utilizing a valid value model that adequately justifies the proposal evaluation process is at the core of this research. N-way sensitivity analysis is not unique to the JIEDDO decision model because most decision problems contain more than two values. Even the simplest day-to-day decisions require an assessment of a number of different values. N-way sensitivity analysis is required to provide a comprehensive evaluation of the alternatives for a decision problem prior to implementation.

I.C. Research Scope

This thesis will evaluate the validity of the proposed JIEDDO Proposal Value Model. As such, this research addresses the following questions: *Does the value model adequately reflect JIEDDO's decision process? Secondly, given the dynamic environment of the current war, how confident can we be in the model's ability to continually and effectively screen proposals based on JIEDDO's current values?* To address the first question, the author will utilize multivariate techniques, specifically

Discriminant Analysis, to investigate JIEDDO's ability to make consistent decisions within their proposal evaluation process. Once it has been determined that the JIEDDO Proposal Value Model effectively screens proposals in nearly the same manner as that of a panel of decision makers, it is possible to proceed with the second question.

In order to address the model's robustness, the author will investigate the weighted values that the model utilizes to evaluate a set of given proposals. By consolidating and applying n-way sensitivity analysis techniques, specifically in the areas of math programming and Multivariate Analysis, the author will propose a consistent sensitivity analysis image profiling technique.

I.D. Assumptions

Value focused thinking models are carefully developed by decision analysts who work with the decision maker to encapsulate adequately the values for the decision under consideration. This research assumes that the creators of the original JIEDDO Proposal value model worked with the appropriate decision maker and subject matter experts to identify all of the values pertaining to the decision problem at hand. Furthermore, the assumption is that all of the values for the decision have been captured. Lastly, this research assumes the appropriate application of the value focused thinking methodology (VFT) requirements to include small size, operability, mutual exclusivity, preferential independence, and collectively exhaustive for the JIEDDO Proposal Value Model.

I.E. Thesis Organization

The remainder of this thesis contains four chapters organized in the following manner: Chapter 2 consists of a thorough literature review of DA, VFT methodology, value hierarchy construction, weighting, sensitivity analysis, as well as field applications.

Chapter 3 of this document presents a discriminate analysis model validation technique. Additionally, the chapter outlines and presents a new n-way sensitivity profiling technique. Chapter 4 consists of the results and analysis that comprise the aforementioned discriminant analysis techniques and the in-depth n-way sensitivity analysis as it pertains to the JIEDDO proposal solicitation process. Lastly, chapter 5 discusses relevant conclusions and explores opportunities for future research.

II. Literature Review

II.A Introduction

The purpose of the literature review is to conduct an extensive study on the various components of DA to include VFT, value hierarchy construction, weighting, sensitivity analysis as well as the details surrounding the JIEDDO proposal selection decision problem. A thorough understanding of the JIEDDO decision model is rooted in DA methodology. The JIEDDO value model utilizes an additive value function to model the importance of a series of values sought in the submitted proposals. Each of the identified values is assigned a weight that captures its relative importance for the decision problem. An evaluation of the sensitivity of the weights provides insight into the robustness of the model itself.

II.B Decision Analysis

Decision Analysis originated during the 1950s when Robert Schlaifer introduced some of the analytical techniques in his book *Analysis of Decisions under Uncertainty* (Skinner, 1999, 17). Corporate decision makers in our current society utilize DA because they recognize its usefulness in the decision making process (Skinner, 2001, 9).

According to Clemen, before we can begin to apply any methodology to a specific decision problem, the analyst must first identify a decision maker who is appropriate for the decision and possesses the proper authority thereof (2001). After identifying the DM, it is possible to work with them to determine the values and objectives that relate to the decision in question (Clemen, 2001, 21). Clemen clarifies the distinction between objectives and value, stating "An objective is a specific thing that you want to achieve…An individual's objectives taken together make up his or her values" (2001, 22). While most people subconsciously make decisions for their day-to-day life based on their values, we cannot guarantee the selection of the best alternative unless we conscientiously apply a specific methodology that is a repeatable.

Based on the decision problem, decision analysts apply one of two different methodologies to decision processes where single dimensional value functions are involved--Value Focused Thinking (VFT) or Alternative Focused Thinking (AFT). Keeney explicitly differentiated between VFT and AFT in *Value-Focused Thinking: A Path to Creative Decisionmaking*, "Value-focused thinking involves starting at the best and working to make it a reality. Alternative-focused thinking is starting with what is readily available and taking the best of the lot" (1992, 6). As a result, VFT first approaches the decision problem by identifying all of the values relating to the decision. The idea in VFT is to vocalize the desire for an alternative to possess a certain set of values, and investigate the feasibility of producing one. AFT on the other hand, uses the available alternatives as the starting point for the decision process. AFT will identify the best alternative out of a list of provided alternatives.

II.C Value Focused Thinking

The appeal to VFT is its ability to challenge the DM to produce a highly desirable alternative. According to Keeney in *Value Focused Thinking: A Path to Creative Decisionmaking*, the process involves "two activities": "Decide what you want and then figuring out how to get" (1992, p. 4). After properly identifying the DM's values and then arranging them using affinity grouping or some other technique, it is possible to determine the means by which to measure the values (Knighton, 2008). Next, the analyst applies the weights in order to score the alternatives based on an additive value function created using the weighted sum of the DM's previously identified values. The proposed alternatives then receive a score based on the characteristics they possess in relation to the DM's values. Ideally, the generated alternatives possess qualities or characteristics that form the most appealing solution (Keeney, 1992).

II.D Value Hierarchy Creation

Upon deciding to apply VFT methodology to the decision problem, it is important to construct a value hierarchy that adequately models the problem under consideration. According to Keeney, four steps describe value hierarchy creation:

> The first is to work with a decision maker to determine the set of objectives that are appropriate for the decision under consideration. Second, the analysts define attributes that accurately measure how well the objectives are met. Third, a reasonable structure or hierarchy combines the varying attributes in an orderly manner. Lastly, the hierarchy is verified and its reasonability is examined to determine compatibility with the situation at hand (Keeney, 1992, p. 131).

The analyst works with the DM to extract all of the values for the decision. Grouping the values allows us to consolidate similar values and create tiers for the respective subcategories for each of the values.

In *Strategic Decision Making*, Kirkwood defines a value hierarchy as including evaluation considerations, objectives, and evaluation measures (Kirkwood, 1997, 15). Furthermore, he outlines five properties necessary for creating a value hierarchy: collectively exhaustiveness, mutually exclusivity, decomposability, operability, and small size. The requirement that the model be collectively exhaustive ensures that it contains all relative information for the decision problem. Mutual exclusivity ensures that no two evaluation considerations overlap as to avoid "double counting" (Kirkwood, 1997, 17). In addition to the value hierarchy being collectively exhaustive and mutually exclusive, it is necessary to preserve decomposability, also known as preferential independence. One evaluation measure may be mutually exclusive from another; however, they may not be preferentially independent of one another. Kirkwood proposes the following example to reiterate this point:

> Suppose that a job seeker has as an evaluation consideration economic issues, and has…evaluation considerations…salary, pension benefits, and medical coverage. Notice that these are non-redundant issues, but they may not be decomposable. If there are very good pension benefits, then the value of an additional $5,000 in salary may be less than if the pension plan is poor and the job seeker will need to provide for his or her retirement out of salary (Kirkwood, 1997, 17).

Thus, preferential independence serves a significant contribution to the architecture of the value hierarchy.

Next, the operability of the value hierarchy describes the intended audience's ability to understand the model. By preserving operability, the analyst ensures the transferability of the model details to the decision maker or another key figure (Knighton, 2008). This individual is then able to relay the details of the decision problem and value hierarchy construction over to the public whose acceptance is crucial to the implementation of the decision.

Lastly, according to Kirkwood, the size of the value hierarchy is of key importance. It is easier to communicate a small value hierarchy to a variety of audiences, than it is to communicate a large hierarchy (Kirkwood, 1997, 18). Furthermore, creating a small value model often makes it easier to conduct analysis and interpret results.

II.E Weighting

Once the value hierarchy is constructed, Clemen and Reilly suggest that a trade off is made between varying objectives. They introduce weights to determine the exact trade off. Furthermore, they require that the weights appropriately reflect "the relative value" of going from best to worst on each scale for a particular attribute (2001). Thus, weights reflect the DM's preference.

In *Strategic Decision Making*, Kirkwood provides a detailed discussion for determining the weights for a given value model. The value function for a given decision problem with n-different evaluation measures is defined in Equation 1 below.

Equation 1 (Kirkwood, 61)

$$v(X_a, X_b, X_c, \dots X_n) = w_a v_a(X_a) + w_b v_b(X_b) + w_c v_c(X_c) + \cdots + w_n v_n(X_n)$$

X_i = evaluation measure for the i^{th} value
w_i = weight on the i^{th} evaluation measure
$v_i(X_i)$ = single dimensional value functions over each of the i measures
i = a particular value

The importance of a given evaluation measure is denoted by the assigned weight, w_i. Those values that possess a relatively high weight signify a greater level of importance for the decision problem. As a result, selected alternatives typically have highly desired characteristics. However, the total score determination is dependent upon the sum of the weighted single dimensional value functions.

Kirkwood describes the technique of swing weighting as a tool for adequately determining weights. It is necessary to order the increments in value by increasing or "swinging" each of the evaluation measures from least desirable to most desirable (Kirkwood, 1997). After organizing the values incrementally in order of importance, quantitatively scale each of the value increments as a multiple of the smallest value increment (Kirkwood, 1997). Once this value referencing determination is complete each of the scaled weights are summed to 1 and the weight for the least valuable measure is determined (Kirkwood, 1997).

This swing weighting technique is examined in an example for the characteristics sought in a car prior to purchasing. We may consider the following: safety rating, color, size. Now, ordering these values incrementally from least preferred to most preferred, we have: color, size, safety rating. Color receives a weight of k. Now, the decision maker determines how much more they prefer having the vehicle size of choice over that of color choice. For illustrative purposes, the decision maker says 2*k. Next, we determine how much more important is the value of safety rating over that of car color. The decision maker responds 4*k. Following Kirkwood's procedure for determining the single dimensional value function, we have the following calculations:

$$k + 2k + 4k = 1$$

$$7k = 1$$

Solving the algebraic equation, $k = 1/7$

Thus, the weights for each of the values color, size, and safety rating are 1/7, 2/7, 4/7 respectively.

II.F Sensitivity Analysis

The question of the sensitivity of a decision problem under given pre-determined weights refers to the variables that really make a difference in terms of the decision under consideration (Clemen & Reilly, 2001). Clemen and Reilly present methods for conducting one-way and two-way sensitivity analysis as to see how fluctuating one weight while holding the remaining weights proportionately constant (similarly, altering two weights, while holding the remaining weights proportionately constant) affects the rank order of alternatives for a given decision problem (Clemen & Reilly, 2001).

One-way sensitivity analysis allows us to observe how sensitive the decision problem is by looking for rank changes among alternatives as a single weight fluctuates between zero and one (Clemen & Reilly, 2008). If a rank change occurs from adjusting a weight by a small amount, then the decision problem is sensitive for that particular weight. To illustrate this further, consider one-way sensitivity analysis previously conducted by Dawley, Marentette, and Long on Gap Impact.

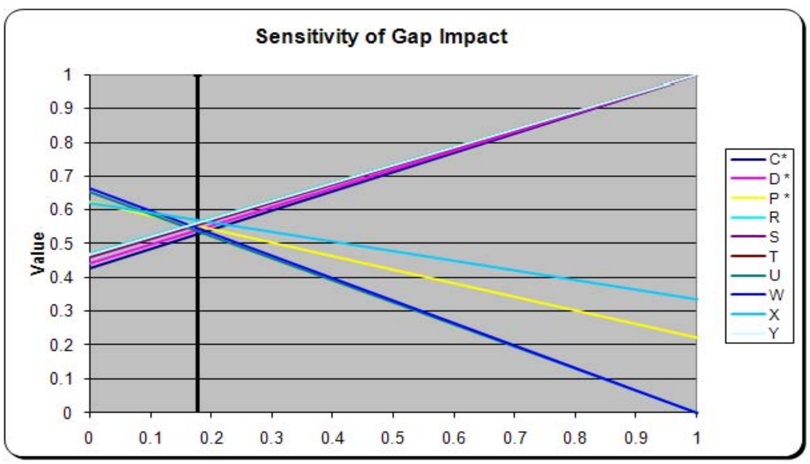


Figure 1: Sensitivity of Gap Impact (Dawley, Marentette, & Long, 2008)

The original global weight for Gap Impact, indicated by the black line above, is 0.176. The analyst observes the sensitivity of ten distinct proposals to varying the weight on Gap Impact between zero and one. As the weight on Gap Impact decreases, the values for Proposals W, X, and P* increase while the values for Proposals R, D*, T, and C* decrease. Thus, rank changes occur resulting from adjustments of the weight for Gap

Impact. The same methodology applies when considering the case of varying two weights simultaneously and holding the remaining weights proportionately constant.

In an article of the application of Response Surface Methodology (RSM) as a sensitivity analysis tool in DA, Bauer, Parnell, and Meyers acknowledge the benefits of performing one-way and two-way sensitivity analyses as a "screening tool" for many problems. However, they suggest that a lack of higher order sensitivity analysis to include n simultaneous weight changes has the potential of excluding a large portion of information that is contained in the model (Bauer, Parnell, & Meyers, 1999). They present RSM techniques using the output of the model as the "response" and its input variables in order to improve the decision model (Bauer, Parnell, & Meyers, 1999). The analysts investigate the "numeric perturbation range" for each variable to determine the region of operability (Bauer, Parnell, & Meyers, 1999, 165). Through the use of a "design matrix", where each row represents a set of experimental conditions, it is then possible to observe n different realizations of the model of interest (Bauer, Parnell, & Meyers, 1999, 165). According to Bauer et al., the requirement for using a Response Surface Paradigm is to identify a response function of the form $y = f(x)$ (1999, 167). Recognizing that multi-attribute preference theory and multi-attribute utility theory allows us to write the value function in this form, they conclude that RSM is appropriately used to determine the sensitivity of the decision problem for n varying weights.

Rios Insua and French provide a distance based methodology to the sensitivity analysis problem for discrete multi-objective decision-making. Through using math programming techniques, they compare alternative a_j with a "possible competitor" a_* (where a_* is the optimal alternative for the current decision problem) (Rios Insua &

French, 1989, 181). The authors use this technique in order to determine by how much weight w can be varied before a_j outranks a_*. Thus, they suggest solving the minimization problem:

Equation 2 (Rios Insua & French, 1989, 181)

$$\min_{w \in S} d(w,\omega)$$
$$\text{s.t. } \Psi_j(w_j) - \Psi_*(w) = 0$$

where:

d: distance metric
w: new weights
ω: original weights
S: constraints on w
$\Psi_*(w)$: score provided for the optimal alternative at new weights w
$\Psi_j(w_j)$: score provided for alternative j at new set of weights w_j

This provides insight as the minimization problem seeks to determine w_j such that a_j and a_* are indifferent (Rios Insua & French, 1989, 181). They take this idea a step further by analyzing several distances ($d_j^1, \ldots d_j^n$) to determine the efficient alternatives of the problem of minimizing these distances accordingly. Thus, they allude to the use of varying distances in n-ways to determine the sensitivity of the weights for a given set of alternatives.

Hughes and Hughes apply n-way sensitivity analysis to the field of medicine in *N-Way Sensitivity Analysis: A Verification and Stability-assessment Technique Completely Subjective Decision Analysis Trees*, published in Medical Decision Making in 1990. The authors present a case for using the absolute mean difference estimation of variance in lieu of the standard deviation calculations of variance for a study looking at the extent to which nurses make "internally consistent and mathematically logical decisions as well as to construct demographic, experimental, and educational profile of the consistent clinical decision makers" (Hughes & Hughes, 1990, 69). While they acknowledge the case for standard deviation calculations of variance in some instances of n-way sensitivity analysis, they acknowledge it's inappropriateness in the context of their decision problem. This justification is based on a very small number of parameters (4 of 83 to be exact) failing to exhibit normality according to the Kolmogrov-Smirnov test (Hughes & Hughes, 1990, 71-72).

In a published article, *Sensitivity Analysis of Additive Multiattribute Value Models*, Barron and Schmidt describe the least squares method for determining the sensitivity of the decision problem to varying weights. They compute the weights $w=\{w_1,w_2,\ldots w_n\}$ to determine the value of the alternative v_n that exceeds that of the current optimal alternative v_* by only a small amount (Barron & Schmidt, 1988, 123). Thus, they intentionally choose weights very near the weights for v_n (1988). Barron and Schmidt compute the L_2-norm calculating the squared deviation of the weights (1988, 123). By applying this least squares method, they conclude that an alternative that surpasses that of the value for the current optimal solution for a given set of weight very near that of the optimal proves to be very sensitive for the decision problem (Barron & Schmidt, 1988, 123).

Ringuest provides an extension of current L_2 metric sensitivity analysis methodology by considering solutions that minimize the L_1 and L_∞–metrics subject to a set of linear constraints (1996, 563). He suggests the L_p-metric as the generalized form of Barron and Schmidt's least squares procedure allowing for a *P* effect on the "relative contribution of individual deviations" (1996). Thus for large values of *P* a larger contribution of individual deviations is considered, while smaller values of P have a less significant contribution to the individual deviations (Ringuest, 1996). Furthermore, such a variation of P, allows for a maximum change in any one multi-attribute value function weight to be achieved when $P = \infty$ (Ringuest, 1996).

In 2008, Marks researched the affects of n-way sensitivity analysis on various courses of action for the Iraq war. His research pertains to the development of a Value Focused Thinking model to score a series of courses of action options. Marks elicits 14 evaluation measures from his team of SMEs to include: the Percentage of Coalition Lost, the Number of Insurgents Crossing, Ethno-Sectarian Violence, Non-sectarian Violent Death Rate, Average Hours/Day, Water Available per Person per Day, Fuel Available per Person per Day, Tons of Supplies Needed, Estimated Number of Members, Willingness, and Addition to the Number of Units at Levels One through Four (each unit level has a separate single dimensional value function) (2008). Upon eliciting these values, Marks worked with the team to extract weights that would appropriately reflect that of a Combatant Commander who faces selecting one from a series of courses of action. The weighted value function or additive value function allowed the team to score a series of 10 different courses of actions based on the value model. From these scores, Marks developed a ranking of most preferred course of action to least preferred course of action.

While the ranking of courses of action proved insightful based on the values defined in the model, questions remain as to the level of confidence a Combatant Commander can have in utilizing a top ranked alternative. Marks acknowledges that the dangers of selecting the wrong course of action can have significant consequences. American troops could be put unnecessarily in harm's way, and civilian and military lives could be lost if a course of action is implemented that did not consider all aspects of the situation at hand (Marks, 2008).

In order to determine the level of confidence that lies in the model itself, Marks recognizes the need to examine the weights assigned to each of the identified values. “Are the weights really a reflection of the decision maker’s preferences” (Marks, 2008)? Recognizing the dynamic environment commander’s face during the current war, Marks seeks to determine if small adjustments of the weights will significantly affect the rank order of the suggested courses of action (2008).

To address these questions, Marks applies math programming techniques to conduct n-way sensitivity analysis on the weights for the Course of Action Value Model. Particularly, he compared the results produced from optimizing the weight change for the L_1, L_2, L_∞ *norms*, sum of squares, as well as a percent change metric (2008). He believes such a comparison will shed light on the sensitivity of the weights themselves and ultimately provide an answer to the questions at hand.

He evaluates the sensitivity of 10 different alternatives, including Self-sustained Agriculture, Training Indigenous Security Institutions, Expelling Al Qaeda-Iraq, Instituting a Military Draft in Iraq, Partial Coalition Withdrawal from Iraq and Full Coalition Withdrawal from Iraq. Marks seeks to reveal the effects of higher order weight variations on these courses of action (2008). In comparing the effects of n-way weight changes, specifically the aforementioned 14 values, Marks determines that half of the alternatives are sensitive (2008). As a result of the generality that is gained from such small weight changes, he recommends using the 1-*norm* as a primary means of determining the overall sensitivity of the weights to conduct sensitivity analysis (Marks

2008). However, he does not discount the use of any one of the remaining four math programming options as an invalid sensitivity analysis technique.

II.G JIEDDO

The Department of Defense formally recognized a growing need for a joint C-IED collaborated effort in February 2006 by establishing JIEDDO. They declared their primary focus as "reducing or eliminating the effects of all forms of IEDs used against U.S. and Coalition Forces, including policy, resourcing materiel, technology, training, and operations, information, intelligence, assessment and research" (Defense, 2006). JIEDDO's ability to counter IEDs effectively is largely a reflection of their ability to engage the public to aid in the response to research and develop C-IED programs.

In order to aid the decision process, in 2008 Dawley, Marentette, and Long developed a value model to define the JIEDDO initiative solicitation process. Recognizing that there is currently no repeatable framework in place to assist JIEDDO in selecting proposals for funding C-IED projects, the authors sought to provide a systematic methodology to the process. Figure 2 shows the complete value hierarchy and the associated weights for each value.

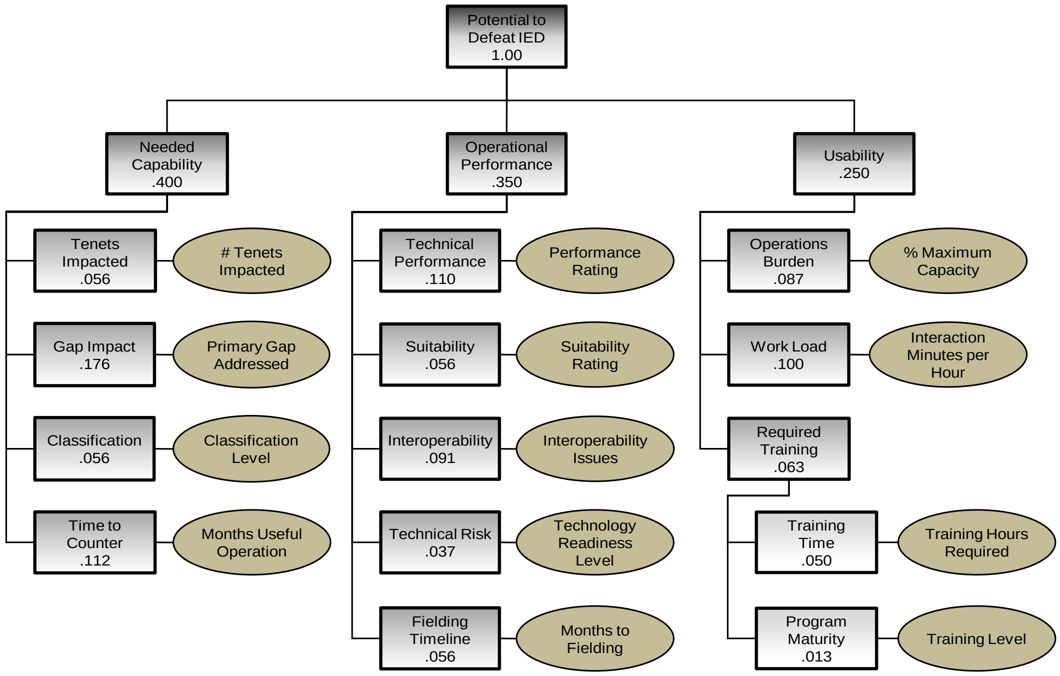


Figure 2: Complete JIEDDO Value Hierarchy (Dawley, Marentette, & Long, 2008)

The "Potential to Defeat IED" contains three first tier values: Needed Capability, Operational Performance, and Usability (Dawley, Marentette, & Long, 2008). The architects of the model used SMEs to extract the weights for each tier of the model to encapsulate the appropriate importance of each evaluation measure adequately.

The information used to score the proposals is extracted from white papers and quad charts provided by the applicant pool at large. The proposal information is extracted from the current proposal solicitation database by means of the Broad Area Announcement Information Delivery System (BIDS) (Dawley, Marentette, & Long, 2008). The information collected via BIDS is traditionally used by a panel of subject matter experts to determine whether the proposed initiative will adequately meet the JIEDDO's C-IED objectives. Through utilizing DA techniques, the models creators present a case for producing a value model that allows JIEDDO to screen proposals rapidly to determine if they are appropriate to enter the initiative evaluation stage.

While the authors have confidence in the value model and its usefulness to JIEDDO, they recognize that advancement is necessary in the way of n-way sensitivity analysis. The team conducts extensive one-way sensitivity analysis to investigate the rank order of the proposal sets. However, the overall scores for each of the proposed initiatives are very close (Dawley, Marentette, & Long, 2008). This poses some concern into the sensitivity of the decision under such small weight changes (Dawley, Marentette, & Long, 2008). Furthermore, the authors recognize that they conducted sensitivity analysis on a discrete set of alternatives. The task of analyzing the sensitivity of the selection of alternatives for a continuous evaluation solicitation process proves to be very challenging (Dawley, Marentette, & Long, 2008).

The sensitivity analysis falls short beyond one-way sensitivity analysis and the implications of altering even two of the weights are limited for this study. Relying on the SME to pinpoint all of the weights exactly may prove troublesome for JIEDDO in the future without the demonstration of extensive model validation.

II.H Summary

This chapter presents research from literature in the areas of DA to include VFT, value hierarchy construction, weighting, and sensitivity analysis. Among the themes of importance is the comprehensiveness of the value model itself, the appropriateness of the weights, as well as the sensitivity analysis for the respective weights. Of particular interest to the analyst team is the decision maker's confidence in the model to identify the decision at hand. Much of the DM's ability to proceed with a particular alternative for the decision replies upon their belief that they are making the correct one for their particular organization. This alternative selection process proves to be of key importance to the leadership at JIEDDO as they determine which proposals they will select for funding. The next chapter expands upon the current methodology for robust sensitivity analysis to include a particular application to the JIEDDO proposal selection value model.

III. Methodology

III.A. Introduction

The purpose of this chapter is to describe the methods used to evaluate the usefulness and robustness of the JIEDDO Proposal Value Model. We recognize that the dynamic environment of the current War on Terror justifiably motivates us to deliver the most effective counter-IED initiatives to the warfighter. Thus, the methods developed in this chapter serve a dual purpose. First, this research will utilize multivariate techniques to answer the following question, "Does the model replicate JIEDDO's decision process?" If the model does in fact adequately replicate JIEDDO's decision process, then it would serve as a rapid screening tool for the pre-proposal investigation process. Second, given the potential for using it as a rapid screening tool, how confident can we be in the model's results? Provided that the model supplies a ranking of proposals from best case to worst case, we want a level of assurance that the rank order is robust. This is determined by observing the affect on rank order under simultaneous weight changes within the model itself.

III.B Discriminant Analysis

Discriminant Analysis is a technique that is used to "classify individuals or objects into mutually exclusive and collectively exhaustive groups based on an observed set of independent variables" (Bauer, Parnell, & Meyers, 1999). In order to apply this technique, the analyst splits the original dataset into a training sample and a validation sample. For data sets with a large number of samples, the training sample is comprised of 2/3 of the observations from the original data while the validation sample comprises the remaining 1/3. The classification of a particular object into a group is determined *a* *priori* by means of a discriminant function defined using the training data (Bauer K. W., 2008). Each classification group possesses a specific discriminant function that describes each group of interest. Next, the approach involves attaching a scalar score to each object in the validation data for each of the defined groups. The analyst calculates the scores by taking a linear combination of the object's attributes. The object becomes a member of the group whose discriminant function produces the highest numerical value when given the object's specific input values. The discriminant function formulation utilized is of the form given in Equation 3 below.

Equation 3 (Bauer K. W., 2008)

$$\hat{d}_i^Q = -\frac{1}{2}\ln\left|S_i\right| - \frac{1}{2}(\underline{X}_0 - \overline{X}_i)' S_i^{-1}(\underline{X}_0 - \overline{X}_i) + P_i$$

where:

S_i: the covariance matrix for the i^{th} population (i.e. accept population, reject population)

$\underline{X}_0$: a specific observation that is seeking to be classified

$\overline{X}_i$: the mean of the observations that comprise the i^{th} population

P_i: the previous population percentage of the i^{th} group

In order to categorize the proposals appropriately into an accept or reject group, the analyst must utilize the information collected for each of the proposals. The 13 values depicted in the JIEDDO "Potential to Defeat" hierarchy shown in Figure 2 capture significant pieces of information for the JIEDDO decision problem. The model's architects provided a brief summary of these 13 values in Table 1.

Table 1: JIEDDO Values (Dawley, Marentette, & Long, 2008)

Variable	Definition
Tenets Impacted	Answers the question, "Does this proposal impact one or many tenets?" This value allows the hierarchy to capture the synergistic value of a solution that impacts more than one tenet.
Gap Impact	JIEDDO establishes prioritized capability gaps on a periodic basis with input from the Combatant Commands. Thus, the value of a proposal is directly related to the priority of the gap which it targets.
Classification	How easily can this solution be shared among stakeholders within and outside of DoD?
Time to Counter	How long will it take for the enemy to develop a counter-measure for the system?
Technical Performance	The predicted performance of a system while executing its intended mission.
Suitability	How well the system will perform in its intended environment.
Interoperability	The degree to which a system fits into the existing network architecture, whether it can exchange data with supporting and supported systems, and/or whether it can perform its task without negatively impacting friendly assets.
Technical Risk	JIEDDO is a risk-tolerant organization. They are willing to accept technology risk if it is outweighed by other benefits. However, a mature technology will provide more value than an unproven technology for the same performance.
Fielding Timeline	How soon the solution can be fielded. If a solution can't be fielded in a timely manner it becomes much less relevant to JIEDDO—only 10% of their budget is spent on proposals with a timeline of 3 years or longer. "Fielded" is defined as when the first article of a system is delivered.
Operations Burden	The degree to which the system will impact the capacity of its host environment, e.g. bandwidth required by a collaborative software system, weight for a vehicle or soldier mounted system, or rack space required for server enabled analysis system.
Work Load	This value captures the time requirements that the solution places on the user in an operational environment to ensure that the system continues to operate as expected.
Training Time	How long does it take to train the average user on the solution?

Appendix A contains the detailed proposal information used to score the 30 proposals. We see from the table above that the nature of the proposal data is both categorical and numerical. This proves challenging for conducting discriminant analysis because it is necessary that the discriminant score be produced using numerical data. With categories like Classification Level, which evaluate a proposal based on its status of classified, secret, FOUO, and none, there is not a numerical representation of this measure as it stands. As a result, each of the evaluation measures translates the raw score into their equivalent value by means of the single dimensional value functions. The additive value function that describes this proposal evaluation is given below.

Equation 4 (Dawley, Marentette, & Long, 2008)

$$V(X) = .056v_{Tenets}(x_i) + .176v_{Gaps}(x_i) + .056v_{Class}(x_i) + .112v_{TimeToCounter}(x_i) + .11v_{TechPerf}(x_i) + .056v_{Suit}(x_i) + .091\,v_{Interop}(x_i) + .037v_{TechRisk}(x_i) + .056v_{FieldTime}(x_i) + .087v_{OpsBurden}(x_i) + .1v_{WorkLoad}(x_i) + .05v_{TrngTime}(x_i) + .013v_{TrngMaturity}(x_i)$$

The coefficients that precede the 13 values are the global weights for each of the respective values. The single dimensional value functions, denoted by $v_{Value\_Name}(x_i)$ determine the translated value for each input. As such, $v_{Tenets}(x_i)$ is the value earned for a proposal that has a particular number of tenets, x_i. The analyst extracts the weighted value contribution prior to conducting the discriminant analysis. The image provided in Figure 3 captures this value contribution information for 30 JIEDDO proposals.

Figure 3: Proposal Score Breakdown

The image serves as a pictorial representation of how the JIEDDO value model can be utilized to evaluate and justify proposal selection or rejection. The 30 proposals are ranked according to score. The score reflects a proposal's "Potential to Defeat IED" based on the 13 values identified by JIEDDO SMEs. Each proposal is partitioned according to its contribution to the overall score. The green-yellow-red color scheme is applied independently to each column to show the maximum, median, and minimum contribution that is made to the overall score. Looking at Gap Impact, for example, proposals can achieve a maximum value contribution of 0.176 (green), a median contribution of 0.049 (yellow), and a minimum contribution of 0.000 (red). The contribution amount is reflected by the shading thereof. Thus, Proposals 1, 11, 12, 14, 15, 18, 19, all scored relatively well for Gap Impact. Applying this green-yellow-red color scheme to each value (column) provides a clear picture of how well each proposal scored compared to its competitors for each identified value. This serves as a useful pictorial representation and justification tool for organizations like JIEDDO, who are required to show accountability in their decisions.

After translating the data into its constituent weighted value contribution, it is possible to proceed with the analysis. Discriminant Analysis aids in the prediction of accepting or rejecting proposals submitted to JIEDDO for evaluation. This research applies Discriminant Analysis techniques to classify the following two JIEDDO proposal population groups: those that are accepted and those that are rejected. By creating a discriminant function for each population group utilizing Equation 3 and validating the results, the author will show that it is possible to predict whether a panel of decision makers will likely accept or reject a proposal. In other words, provided the knowledge of acceptance or rejected status, as well as the variable information for each of the 13 values, it is possible to use the sample data to create a model to predict whether JIEDDO is likely to accept or reject a given proposal. Such discriminant functions serve as indicators of JIEDDO's evaluation thought process.

A confusion matrix indicates the effectiveness of the discriminant function in classifying a particular sample into the appropriate group. The confusion matrix for this particular decision problem describes the proposals that were classified by the discriminant function in the following ways: the proposals that should be accepted and were accepted by JIEDDO, the proposals that should be accepted but were rejected by JIEDDO, the proposals that should be rejected and were rejected by JIEDDO, and the proposals that should be rejected but were accepted by JIEDDO. Such relationships among the data are commonly depicted in the form of the confusion matrix seen in Table 2 below.

Table 2: Confusion Matrix (Dillon & Goldstein, 1984)

		Predicted Membership DF Categorization	
		Accept	Reject
Actual Membership	Accept	N_{1C}	$N_{1\underline{C}}$
	Reject	$N_{2\underline{C}}$	N_{2C}

where, N_{iC} = # of class i classified correctly

$N_{i\underline{C}}$ = # of class i classified incorrectly

1 = Actual Membership accept, 2 = Actual Membership reject

III.C Lachenbruch's Holdout Procedure

Lachenbruch's Holdout Procedure utilizes the aforementioned Discriminant Analysis procedures to provide a discriminant function for a particular observation or holdout. Although the approach for developing the discriminant function and the confusion matrix for Discriminant Analysis and the Lachenbruch Holdout Procedure are the same, a difference exists in splitting the original data set. While Discriminant Analysis uses a 2/3 training set and 1/3 validation set to determine the appropriate grouping for a particular proposal, Lachenbruch uses a N - 1 training set whereby N is the total number of observations in the original data set. The validation set is comprised of one holdout. Thus, the approach is to withhold one observation from the dataset and run the analysis to develop the discriminant function using the remaining observations. Upon identifying the appropriate discriminant function, the analyst runs the single holdout observation through each function to determine to which group the holdout belongs.

The challenges of dealing with a small sample size like that of the 30 proposals contained in the JIEDDO model provide support for using the Lachenbruch Holdout Procedure to conduct the discriminant analysis. This procedure produces a unique discriminant function for the accepted and rejected groups for each of the 30 proposals. As such, the first ranked proposal is the first holdout; the procedure produces a discriminant function for each acceptance and rejection groups utilizing the data for the remaining 29 proposals. Once the two functions are created, proposal one is used to validate their effectiveness. A discriminant score is produced using each the accepted discriminant function and the rejected discriminant function. The proposal belongs to the group whose discriminant function score is the largest. After assigning the proposal to a group, we verify the acceptance or rejection of the proposal to determine how well the function predicted the proposal's status. Next, the first proposal returns to the dataset, the second ranked proposal exits, and the process repeats. The procedure creates a specific set of discriminant functions for this next ranked proposal.

The iterative nature of Lachenbruch's Holdout Procedure allows for a more fitting evaluation of a proposal in accordance with the appropriate accept or reject determination. The confusion matrix for such a process would contain one sample. However, for the sake of clarity, the confusion matrix produced using this technique will utilize the consolidated validation information for each of the 30 functions.

III.D Sensitivity Analysis

The dynamic nature of the enemy to respond under adversity raises the question of how confident we can be in the JIEDDO Proposal Value Model's ability to recommend advancing the proposals that will have the greatest positive impact. Success relies heavily on selecting proposals that will adequately restrict the enemies' ability to react to or counter our defense measures. By examining the development of the JIEDDO Proposal Value Model, specifically the weights placed on the identified values, we will provide confidence in its ability to select and reject proposals appropriately.

The current value model resulted from SMEs extracting JIEDDO's values from within the organization. After completing an extensive evaluation process, the analysts used affinity grouping to identify 13 values for the decision problem. Again, Table 1 details these values and their respective definitions as originally defined by the team of analysts.

The JIEDDO team of analysts elicited weights for each of the provided values using swing weighting. Recognizing the subjectivity of this process, it is necessary to determine the sensitivity of the overall rank order produced via weight changes within the additive value function. By demonstrating the soundness of the suggested model results, JIEDDO decision makers will be able to utilize the model confidently as a filter for selecting or rejecting the proposals. Furthermore, the JIEDDO model will serve as a useful tool in providing detailed feedback to the applicant on where their proposal succeeded (or failed) to meet pre-designated JIEDDO values.

In order to demonstrate the robustness of the model, it is necessary to investigate the sensitivity of the weights themselves on multiple levels. We know from traditional sensitivity analysis that it is common to investigate one-way and two-way sensitivity analyses. This involves observing the rank order as one or two values are adjusted keeping the remaining values proportionately constant. Such analysis has the potential to provide insight into the more dominant values in a given decision problem (Bauer, Parnell, & Meyers, 1999). However, it is equally important to expand sensitivity analysis to include those that consider adjusting three or more weights at a time, thus conducting n-way sensitivity analysis (Marks, 2008).

The previous research conducted by Hunter Marks compared a series of five different n-way sensitivity analysis techniques and investigated their effectiveness. Marks utilized mathematical programming techniques to determine the minimum weight change that can be made across all weights while preserving the rank of a given alternative. Thus, he examined the distance of a given alternative from the remaining population of alternatives in n-space by using the following five math programming techniques: least squares, 1-norm, 2-norm, ∞-norm, and percent change metrics. Although he recommended utilizing the 1-norm for his particular Course of Action Value Model, he recognized that each of the five metrics is useful. As such, his research suggests that it is permissible to choose any one metric to develop and conduct sensitivity analysis for the JIEDDO value model.

This research employs the 2-norm to determine the minimum distance in the weight space between a pair of proposals such that their overall value scores are equal. Thus, we are looking to find a new set of weights such that these new weights, when applied to the additive value function (replacing the original global weights), produce equal scores for the two proposals being compared. For example, consider proposal number one and proposal number four. The objective is to determine the minimum weight change such that the value of proposal one equals that for proposal four. The original global weights are perturbed simultaneously to produce a new set of weights that will achieve this result. We have the following problem formulation.

Problem 3.1 1 (Marks, 2008) Minimize $\sum_{i=1}^{k}(W_i - w_i)^2$

subject to:

$$\sum_{i=1}^{k}(v^A(x_i) - v^B(x_i))w_i = 0 \quad \forall A \neq B$$

$$\sum_{i=1}^{k} W_i = 1$$

$$\sum_{i=1}^{k} w_i = 1$$

$$0 \leq w_i, W_i \leq 1 \quad \forall i = 1...k$$

where:

W_i = the initial weights defined by the decision maker

w_i = the weights found that minimize the measure

$v^A(x_i)$ = value score of attribute i for alternative A

Problem 3.1 1 illustrates measuring the sensitivity of proposals utilizing a pairwise comparison method. Thus, we seek a new set of weights that will force the value of a given proposal A to be equal to that of B. The problem formulation aims to minimize the weight change from the original global weights to the new weights for each of the values. Additionally, each set of weights must sum to one and exhibit non-negativity. Thus, this research examines the distance between two different proposals in n-space, where n is the number of identified values for the decision problem.

While comparing the two proposals, we recognize that the new set of weights will ensure that they have the same value, the new set of weights will, correspondingly, affect the value of the remaining twenty eight proposals. As a result, we acknowledge rank preservation of the remaining proposals is not guaranteed when solving the optimization problem for a specific pair of proposals.

This research applies the 2-norm math programming technique to each proposal. As such, for a set of m different proposals, this optimization problem will be applied a total of m^2 times. However, since this research makes pairwise comparisons, it is given that the minimum distance from proposal A to proposal B is the same as saying the minimum distance from proposal B to proposal A. In addition, the minimum distance from a given proposal to itself is zero. The number of unique pairwise comparisons can be reduces to $(m^2–m)/2$ or $m(m-1)/2$.

In order to consolidate the distance information identified from employing the 2-norm adequately, it is possible to construct an m x m distance matrix where m is the number of proposals whose rank change the author wishes to observe. This research uses the thirty proposals from the currently available data, thereby resulting in 435 unique pairwise comparisons. The matrix contains the distance between two different proposals for all the pairwise comparisons of the proposals' values. The distance matrix produced using the Problem 3.1 1 formulation will resemble that seen in Figure 4.

0	$D_{1,2}$	$D_{1,3}$	…		…	$D_{1,30}$
$D_{2,1}$	0	$D_{2,3}$	…	…	…	$D_{2,30}$
$D_{3,1}$	$D_{3,2}$	0	…	…	…	$D_{3,30}$
…	…	…	0	…	…	...
…	…	…	…	0	…	…
…	…	…	…	…	0	$D_{29,30}$
$D_{30,1}$	…	…	…	…	$D_{30,29}$	0

Figure 4: Distance Matrix

Examining the distances between proposals in n-space where n is the number of variables under consideration (13 for the case of JIEDDO) will ultimately reveal information about the sensitivity of the weights themselves. If a weight change is made, we recognize that it is as minimal as possible as to meet the desired objective. Given that a weight change does occur, we know w_i reflects the newly generated weights. From w_i, we utilize the weighted value function previously defined in Equation 4 with the new weights in order to verify that such a calculation will in fact produce equal scores for proposals.

The distance matrix formulation allows us to observe how far apart proposals are from each other, thereby characterizing the distances between distinct proposals. Conversely, a similarity matrix depicts the similarities between a given pair of proposals (Bauer K. W., 2008). The similarity matrix is constructed using the formulation as shown in Figure 5.

Let S be the similarity matrix produced using the distance matrix D.

Equation 5 (Bauer K. W., 2008)

$$S_{ij} = \frac{1}{1 + D_{ij}}$$

The similarity matrix becomes:

1/(1+0)	1/(1+$D_{1,2}$)	1/(1+$D_{1,3}$)	…	1/(1+$D_{1,30}$)
1/(1+$D_{2,1}$)	1/(1+0)	1/(1+$D_{2,3}$)	…	1/(1+$D_{2,30}$)
…	…	1/(1+0)	…	…
…	…	…	1/(1+0)	1/(1+$D_{29,30}$)
1/(1+$D_{30,1}$)	…	…	1/(1+$D_{30,29}$)	1/(1+0)

Figure 5: Similarity Matrix

The similarity matrix in Figure 5 resembles that of a correlation matrix. In fact, the correlation matrix has often been characterized as a similarity matrix because it applies the pairwise comparison technique to depict how closely related a given set of variables are to each other (Bauer K. W., 2008). As such, perfectly correlated variables have a correlation factor equal to one while those variables that are independent of each other possess a correlation factor equal to zero (Bauer K. W., 2008). Once the similarity matrix is formed from the distance matrix, this research will investigate the sensitivity of the proposals by employing Factor Analysis to extract more information about the population set of interest. More specifically, the author will use Factor Analysis to examine clustering among the various JIEDDO proposals.

According to Dillon and Goldstein, Factor Analysis seeks to "simplify complex and diverse relationships that exist among a set of observed variables by uncovering common dimensions or factors that link together the seemingly unrelated variables" (Dillon & Goldstein, 1984). Factor Analysis thereby relates to this research's purpose to determine the common relationships among seemingly different proposals for the JIEDDO value model proposal evaluation process. Dillon and Goldstein provide the following formulation for the factor-analytic model.

Equation 6 (Dillon & Goldstein, 1984)

$$X = \Lambda f + e$$

where:

X = p-dimensional vector of observed responses, $X' = (x_1, x_2, x_3, x_4, \ldots, x_p)$
f = q-dimensional vector of unobservable variables called common factors,
$f = (f_1, f_2, f_3, \ldots f_q)$
e = p-dimensional vector of unobservable variables called unique factors,
$e = (e_1, e_2, e_3, \ldots e_p)$
Λ = pxq matrix of unknown constants called factor loadings

The number of retained factors and their underlying variable contribution is determined using the loadings matrix. Dillon and Goldstein describe the loadings accordingly, stating "they tell us which variables are involved in what factor and to what degree" (Dillon & Goldstein, 1984). The loading matrix for the similarity matrix is calculated using Equation 7.

Equation 7 (Bauer K. W., 2008)

$$L = \sqrt{e_{value}} * e_{vector}$$

where:

L = loading matrix
e_{value} = eigenvalue
e_{vector} = eigenvector

From the loading matrix, this research will use a heuristic to determine the "pattern matrix" (Dillon & Goldstein, 1984). This procedure necessitates starting with the first variable and the first factor and moving horizontally across the factors of the loading matrix and selecting the loading with the largest positive or negative contribution to the given factor (Dillon & Goldstein, 1984). Next, we consider the second row (or proposal for this research) looking for the greatest positive or negative contribution to a given factor and circling it appropriately. This process continues for each of the 30 proposals that comprise the similarity matrix used in this analysis.

Dillion and Goldstein describe the variable loading examination process, "After all the variables have been considered, examine each circled loading for significance" (1984). They suggest assessing the statistical or practical significance as it applies. As such, the statistical significance as it applies to small sample sizes like that for JIEDDO would have to be greater than +/- 0.30 in order to be deemed significant (Dillon & Goldstein, 1984). A practical evaluation of significance would imply setting a rule for a minimum amount of accountable variance for a given factor. For this research, we will assess the significance using the statistical significance evaluation suggested. Once this process is complete, the examination of remaining "insignificant" variables will be reviewed and assessed to determine their relevance for a given factor. Lastly, the author will extrapolate meaning from the pattern of factor loadings by assigning a name to the factor that incorporates the variables reflected thereof.

The loading matrix produced using this method is a "particular interpretation" of the data (Dillon & Goldstein, 1984). Once this process is complete and the loadings have been calculated in their original form, it is then possible to rotate the loading matrix. Rotating the factor loadings matrix permits us to view the factors from a different perspective. This perspective is allows us to interpret the factors from a varying degree of directions.

The three orthogonal rotation methods available to use for this analysis consist of varimax, quartimax, and equimax methods (Dillon & Goldstein, 1984). The objective of the varimax method is to rotate the factors in a manner that will achieve the largest squared factor loadings for a given factor. The quartimax method rotates the factors by spreading the variables so that there is a one for one ratio between a given variable and a factor. Dillon and Goldstein describe this method as that which is very difficult to accomplish (1984). The third method, the equimax method, consists of rotating until a "simple structure with respect to the rows and columns" is achieved (Dillon & Goldstein, 1984). The varimax method is the most common of the rotation techniques and this research uses it to determine key factors for the JIEDDO model.

The clusters produced via Factor Analysis permit us to make additional observations about the proposal groupings themselves. For example, suppose that the Factor Analysis generates three clusters of proposals and each proposal is then grouped according to the cluster to which it belongs. Thus, we have a set of proposals in the first cluster, a (different) set of proposals in the second cluster, and the remaining proposals clustered in the third. After clearly identifying the clusters, it is important to look for common characteristics among the proposals that fall within a given cluster. There is a reason why such proposals are grouped; the research team must identify these reasons. A cluster of proposals that rank in the top third with respect to their overall value score indicates similarities among the proposals themselves. Correspondingly, accepting all proposals except one within a cluster suggests that there is inconsistency within the evaluation process.

Using this information, the research will utilize the original distance matrix to determine the average distance between proposals within a given cluster as well as find the average distance between clusters. By determining the average distance within and between clusters, this research seeks to demonstrate the significance of being in one cluster as opposed to another. Figure 6 shows a pictorial view of this example.

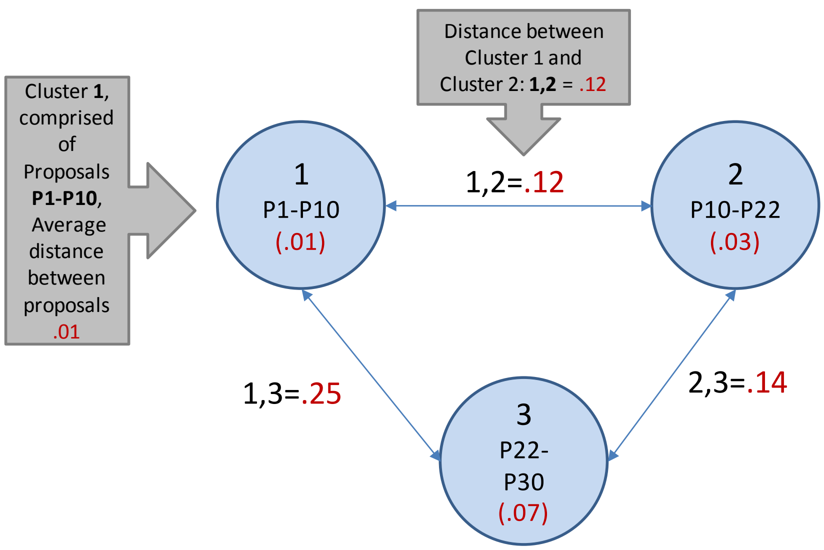


Figure 6: Sample Cluster Analysis

This sample clustering analysis illustrates the relative distances within the weight space both within and between clusters. As such, we see that the average distance between proposals within a given cluster is much smaller than that seen between the clusters themselves. Take cluster two, for example. We see that the average distance between any two proposals within in the set (proposal 10 to proposal 22) is 0.03.

However, the average distance between clusters one and two, and two and three is 0.120 and 0.140, respectively.

Alongside the overview of proposals sensitivity provided by observing clustering, additional insight is gained by further investigating the new weights generated from the minimum weight change analysis. This research will use imaging to illustrate the analysis problem by depicting the weight changes that produce the minimum distance such that two given proposals considered indifferent in value.

Image comparisons are provided for both the percent weight change with respect to the original global weights and the actual weight change values themselves. An image is generated for each proposal. The images are formed by utilizing the new weights provided via the pairwise comparison metric described in Problem 3.1.1 and is exemplified by the 15th ranked proposal in the set. A 30 by 13 matrix is produced whereby each row contains the new weights generated for each of the 13 values when the 15th ranked proposal is compared to a proposal whose rank designation is equal to that of the row in which it resides. From this information, the percent weight change is calculated with respect to the original global weights for each value and thereby providing the positive or negative change for each of the 13 weights.

Once this is complete, the imaging is produced via a coloring effect which is coded using the standard red and green metric. The largest positive and negative weight changes are identified by using a percentile metric where all of the weight changes are compared with the most negative weight change falling at the zero percentile and the most positive weight change occurring at the 100th percentile. As such, we generally find that dark green indicates a positive percent weight change and red indicates a negative weight change. A different color shade is attributed to every fifth percentile captured. This imaging technique is applied to both the percent weight change values as well as the actual weight change for all of the proposals under consideration. An example of the imaging technique utilized in this research is shown in Figure **7**.

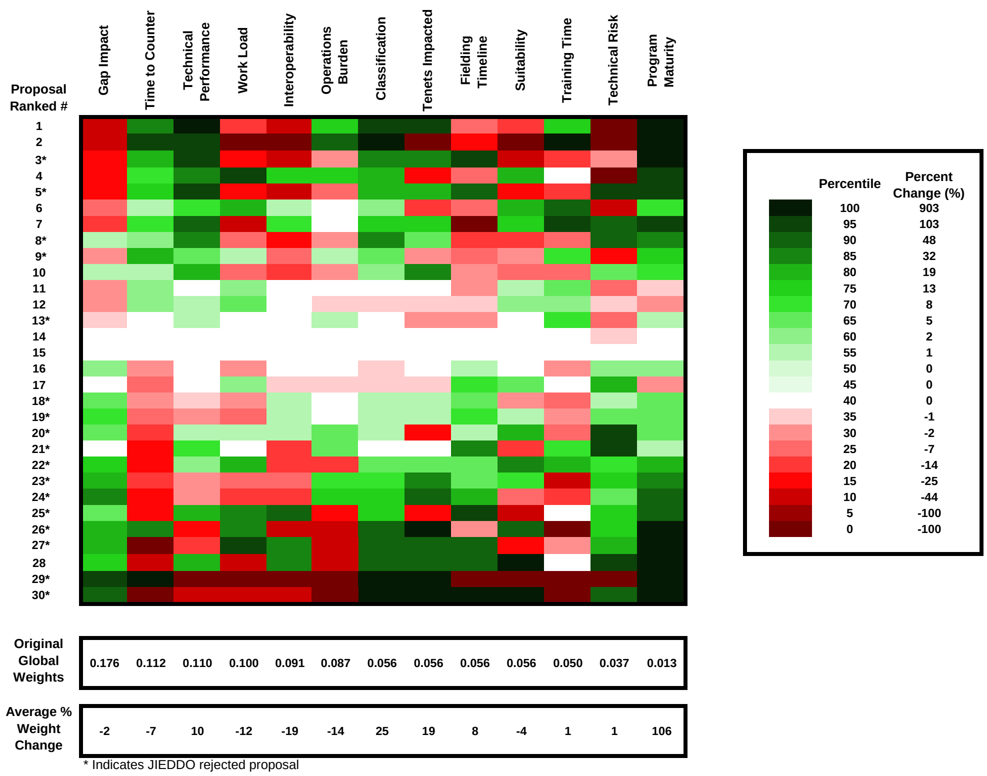
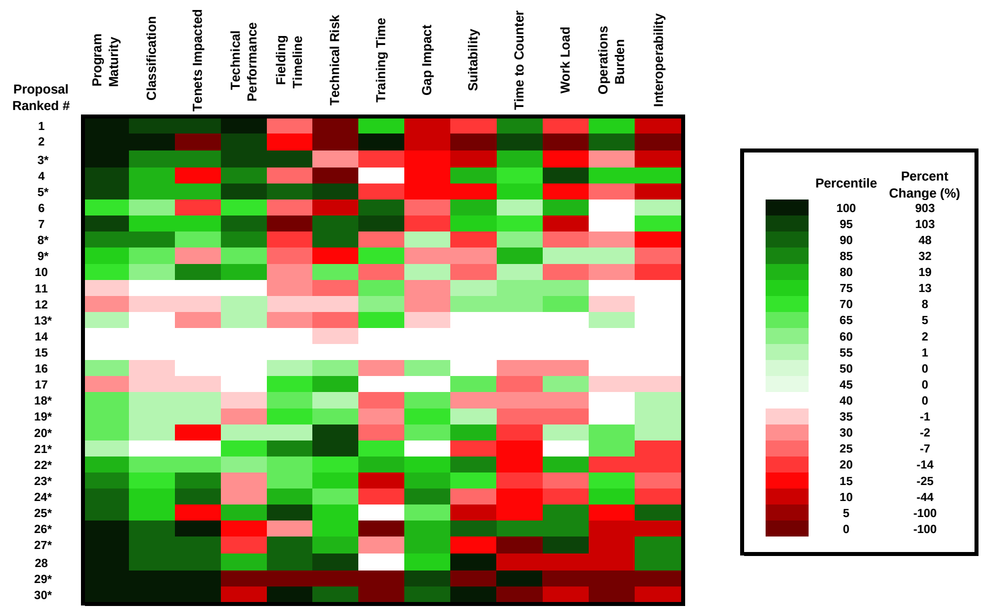


Figure 7: Proposal #15 Percent Change

Figure 7 above depicts the image generated for proposal 15. The columns of the image represent the 13 values arranged according from largest to smallest global weight. Each value's respective global weight is shown directly below the generated image. The percent weight change from the original global weights to the new set of weights that produces equal value to that of proposal 15 is shown for each row of the matrix. For example, consider the comparison of proposal 15 to proposal 1. Based on the characteristics that define proposal 15, the weights for Gap Impact, Work Load, Interoperability, Fielding Timeline, Suitability, and Technical Risk would need to decrease simultaneously for proposal 15 to yield a total score equal to that of proposal 1 as shown. Additionally, the weights for Technical Performance, Program Maturity, Tenets Impacted, Classification, Operations Burden, Training Time, as well as Time to Counter would need to increase. From the image shading, we observe that Technical Performance, Program Maturity, and Technical Risk are among those with the largest percent weight change (as denoted by the color intensity). Furthermore, we see from the suggested percent weight changes that proposal 15 exhibits value strength when compared to the top ranked proposal in Program Maturity, Technical Performance, Tenets Impacted, and Classification level. Conversely, weaknesses surface in Technical Risk, Gap Impact, and Interoperability.

Looking at proposal 15's neighbors, proposal 14 and proposal 16, we notice only slight variations among varying values. These small percent weight changes indicate weight sensitivity when looking at proposals most near that of the observed proposal. We gain additional insight by generating this image under a percent weight transformation. The transformed image is produced by taking the average percent weight change for each of the respective values and sorting them from most positive to most negative average percent weight change. This is shown for proposal 15 in Figure 8.



	Program Maturity	Classification	Tenets Impacted	Technical Performance	Fielding Timeline	Technical Risk	Training Time	Gap Impact	Suitability	Time to Counter	Work Load	Operations Burden	Interoperability
Original Global Weights	0.013	0.056	0.056	0.110	0.056	0.037	0.050	0.176	0.056	0.112	0.100	0.087	0.091
Average % Weight Change	106	25	19	10	8	1	1	-2	-4	-7	-12	-14	-19

* Indicates JIEDDO rejected proposal

Figure 8: Proposal #15 Percent Change (Sorted Vertically)

Based on the average percent weight change metric, the figure illustrates that the most positive weight change occurs for Program Maturity and Classification. In general, the most negative weight change occurs for Work Load, Operations Burden, and Interoperability. Observing the percent weight changes in this manner allows for a broader view of which values dominate a given proposal's overall score.

The proposal evaluation imaging process can be taken a step further by analyzing the images for the actual weight changes. Actual weight change imaging allows us to see by how small or large a weight fluctuation is occurring. Figure 9 and Figure 10 depict the actual weight changes that are occurring for proposal 15 for each pairwise comparison.

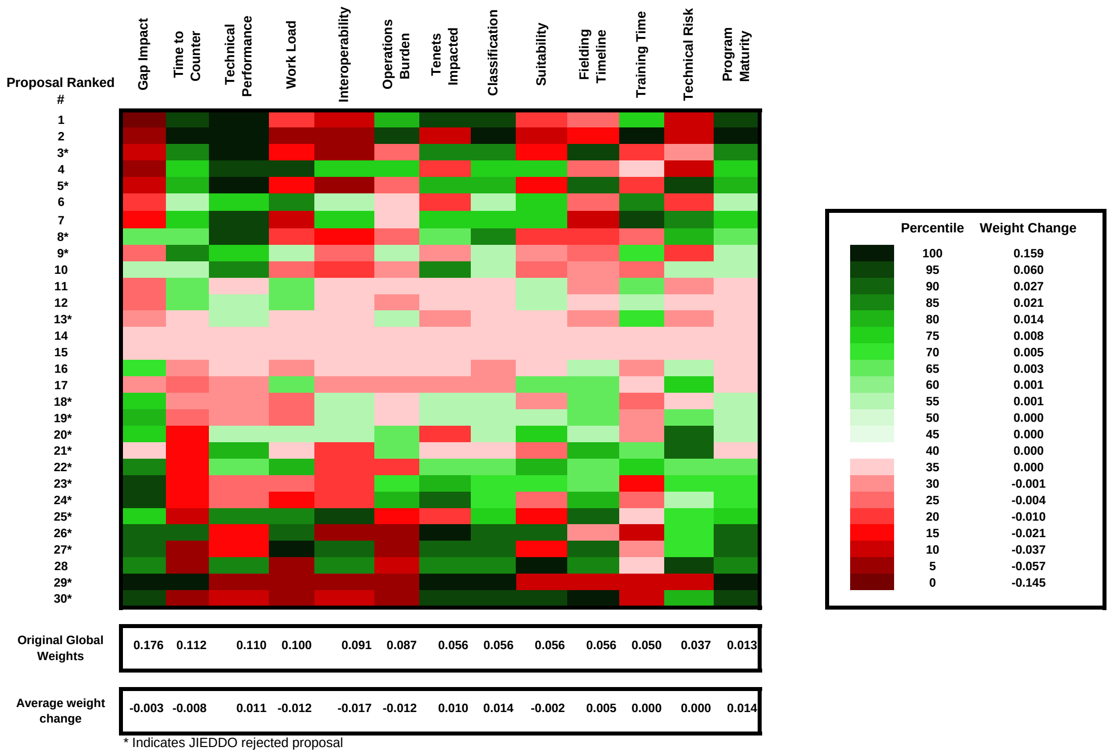


Figure 9: Proposal #15 Weight Change

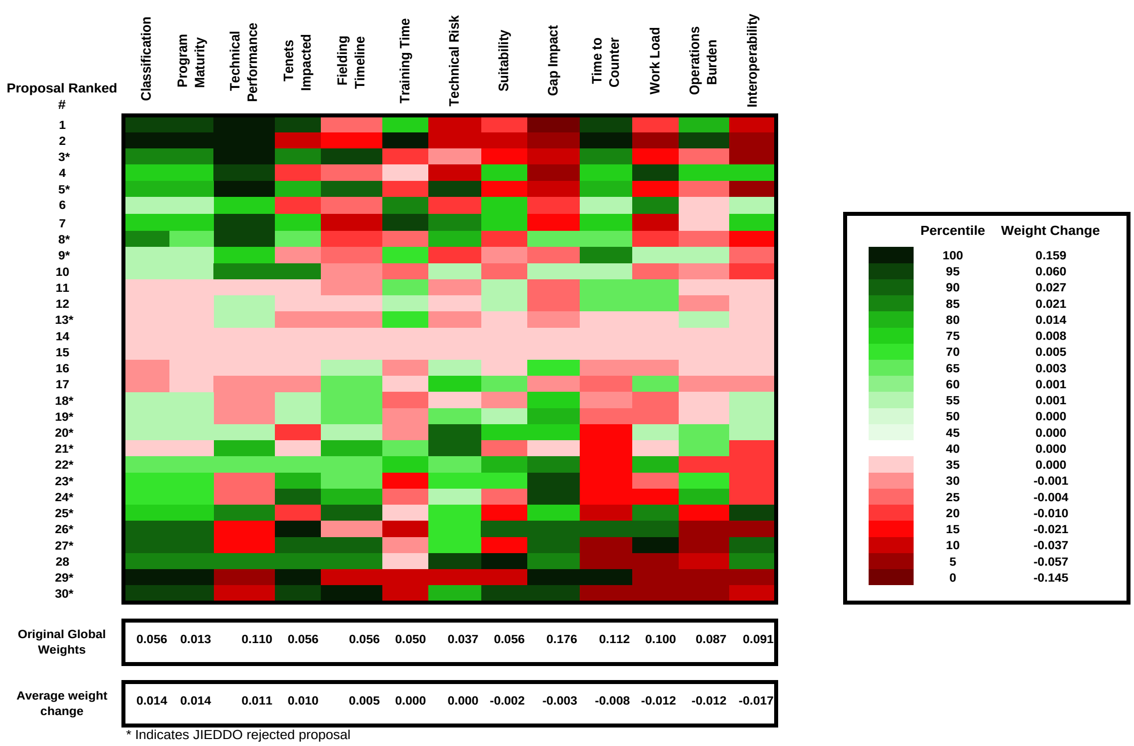
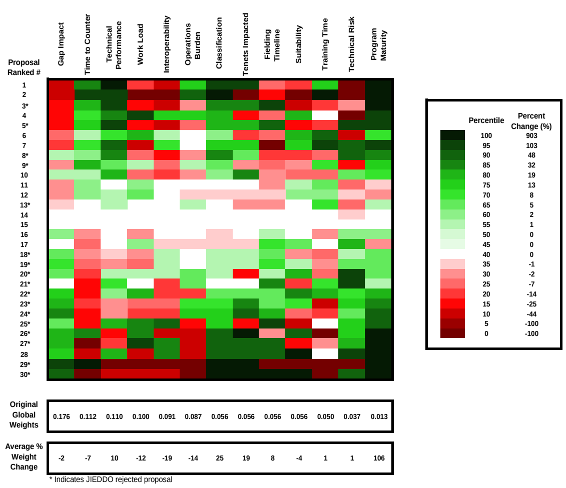


Figure 10: Proposal #15 Weight Change (Sorted Vertically)

The percent weight change and actual weight change images for Proposal 15 exhibit similar patterns in behavior as shown in the side by side view below. The weight on Gap Impact would need to decrease while the weights for Time to Counter and Technical Performance increase in order for a rank change to occur between proposal 15 and those ranked above it. Conversely, the weight for Gap Impact would increase while the weights for Time to Counter and Technical Performance decrease for proposal 15 to move down in the ranks. Thus, we generally observe a horizontal mirroring effect for the percent weight change and actual weight change images for a given proposal.



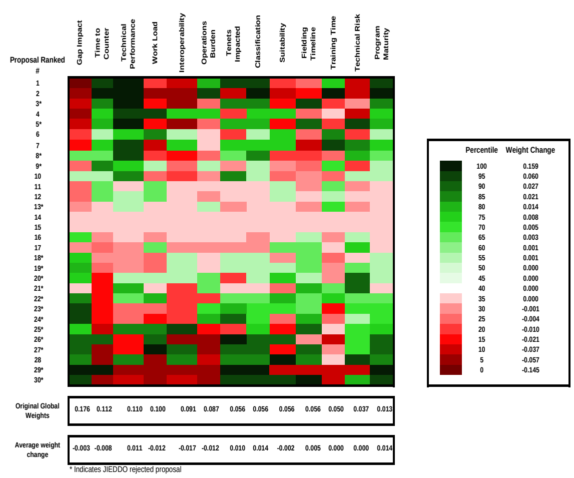


Figure 11: Proposal 15 Percent Change Figure 12: Proposal 15 Weight Change

Again, comparing the transformed (sorted) images for each percent and actual change, we observe a vertical mirroring affect.

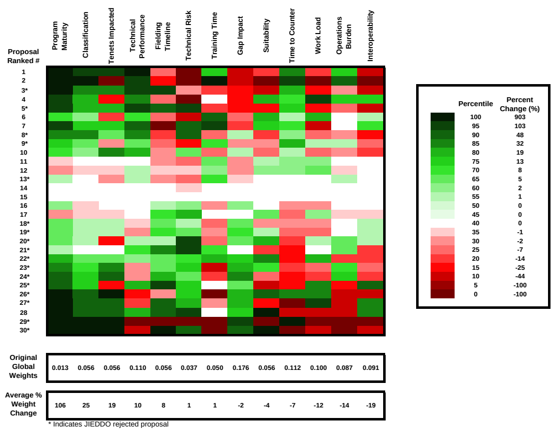


Figure 13: Proposal 15 Percent Change (Sorted Vertically)

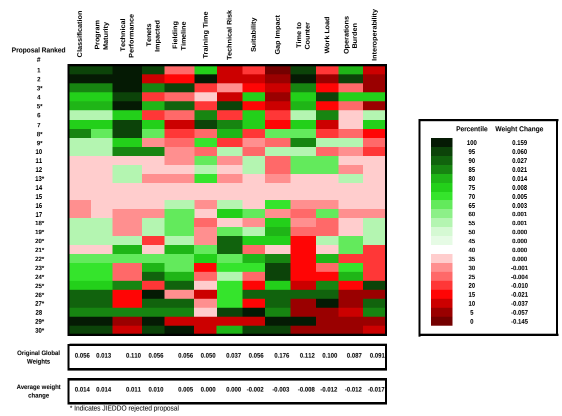


Figure 14: Proposal 15 Weight Change (Sorted Vertically)

The transformed images shed light on the average positive or negative weight change. For proposal 15, the average change among nearly all proposals is positive for Classification and Program Maturity. The majority of proposal comparisons for proposal 15 indicate decrease weight changes for Interoperability.

III.E Summary

This chapter reviewed the methodology employed in validating the model's ability to predict JIEDDO's decision making though process well as the decision problem's sensitivity to simultaneous perturbations in the model's weights. More specifically, the use of multivariate techniques such as Lachenbruch Holdout Procedure for Discriminant Analysis was discussed in detail to develop a function that would reflect the acceptance and rejection proposal populations. Factor Analysis was utilized in combination with math programming techniques to collect additional insight regarding the sensitivity of the weights for the decision problem. The results for this applied methodology as it pertains to the JIEDDO value model are contained in the following chapter.

IV. Results and Analysis

IV.A Introduction

This chapter explains the results of the research involving the validation and weight sensitivity for the JIEDDO value model. In particular, it provides detailed discussion and analysis of the model's robustness based on the methodology described in Chapter 3. First, the author will investigate the model's ability to predict the JIEDDO's decision process by applying the Lachenbruch Holdout Procedure. Second, the author will evaluate the sensitivity of the model under simultaneous weight changes to indicate the level of confidence in the model's results.

IV.B Lachenbruch's Holdout Procedure

The iterative nature of the Lachenbruch Holdout Procedure facilitates splitting the original data set in a manner that accounts for a larger number of observations. A discriminant function is determined for the accept group as well as the reject group using a training sample comprising of N-1 observations (where N is the total number of observations). The remaining observation, or holdout, is then validated using the discriminant functions produced by the training data. For the 30 proposals used in this research, the training group comprises of 29 samples and the validation group comprises of 1 sample. A separate discriminant function is produced for each proposal utilizing the remaining 29.

A confusion matrix can be provided for each one of the validation observations, or holdouts. However, for the sake of clarity, the consolidated result produced after applying this technique to each of the 30 JIEDDO proposal evaluation processes is shown in the confusion matrix in the Table 3.

Table 3

		Predicted Membership DF Categorization	
		Accept	Reject
Actual JIEDDO Decision	Accept	13	0
	Reject	0	17

The associated apparent error rate (APER) is:

$$APER = \frac{N_{1\bar{C}} + N_{2\bar{C}}}{n_1 + n_2} = \frac{0}{30} = 0$$

where, N_{iC} = # of class i classified correctly

$N_{i\underline{C}}$ = # of class i classified incorrectly

1 = Actual Membership accept, 2 = Actual Membership reject

n_1 = total number of samples in group 1

n_2 = total number of samples in group 2

The ability of a discriminant function to predict the acceptance or rejection of a proposal that has been withheld from the population is promising. The 100% hit rate justifies using the Lachenbruch Holdout Procedure to predict the status of a proposal. Furthermore, it serves as motivation that the discriminant functions and JIEDDO decision are compatible. Thus, this research proves it is possible to create a discriminant function that predicts JIEDDO's decision process. However, the question remains as to whether or not their decision process is consistent with their values as expressed in the value model.

This inconsistency is demonstrated by the proposal scores and ranks in Table 4. JIEDDO rejected five proposals in the top half. Meanwhile, they accepted proposal V, which ranked third from the bottom. This begs the question as to the model's validation.

More specifically, it raises the question of how confident should we be in the model's ability to reflect the decision based on the predefined specified values.

Table 4: Proposal Value Model Results

Proposal Name	Value Model Score	Rank
DD	0.822	1
BB	0.727	2
F*	0.683	3*
CC	0.672	4
E*	0.672	5*
AA	0.620	6
Z	0.613	7
J*	0.599	8*
B*	0.584	9*
X	0.576	10
R	0.565	11
T	0.563	12
P*	0.561	13*
Y	0.561	14
S	0.555	15
W	0.554	16
U	0.539	17
D*	0.539	18*
C*	0.528	19*
L*	0.502	20*
I*	0.491	21*
G*	0.488	22*
Q*	0.477	23*
O*	0.447	24*
N*	0.420	25*
A*	0.401	26*
K*	0.387	27*
V	0.367	28
M*	0.364	29*
H*	0.170	30*

* Indicates JIEDDO rejected proposal

Further investigation proves that all four rejected proposals in the top half are research and development (R&D) proposals. As a result, F*, E*, J*, and B* scored "artificially high" in the areas of Time to Counter, Technical Performance, Suitability, Interoperability, Operations Burden, Work Load, and Training Time (Dawley, Marentette, & Long, 2008).

A team of AFIT scored all of the proposals provided for this research. In regard to the R&D proposals, according to the analysts that scored the proposals, "their deliverable was a research paper instead of a prototype system." (Dawley, Marentette, & Long, 2008) This fact made scoring very difficult for the aforementioned evaluation measures. For Interoperability, Dawley, Marentette, and Long define this measure as, "The degree to which a system fits into the existing network architecture, whether it can exchange data with supporting and supported systems, and/or whether it can perform its task without negatively impacting friendly assets" (2008). Based on this definition, it would be easy to say that the R&D paper topics would not "negatively impact friendly assets" because it is not an actual system. As a result, the analysts gave it the most valuable score for this particular score. In fact, all of the proposals received the most valuable score for each of the aforementioned values as they apply to the situation. It is for this reason, that the R&D proposals produced inflated value model scores. The nature of the R&D proposals end product being that of a research paper, vice a C-IED "prototype system", makes utilizing the model for their evaluation inappropriate (Dawley, Marentette, & Long, 2008). As a result, this research cannot support the evaluation of R&D proposals using the current JIEDDO Proposal Value Model. A new model is necessary for the evaluation of R&D proposals. The aforementioned four rejected proposals in addition to one that had been accepted (DD) were recommended for removal from model consideration (Dawley, Marentette, & Long, 2008).

Table 5: Proposal Value Model Results (R&D removed)

Explanation	Proposal Name	Score	Proposal Status
	BB	0.727	Accept
	CC	0.672	Accept
	AA	0.620	Accept
	Z	0.613	Accept
	X	0.590	Accept
	R	0.565	Accept
	T	0.563	Accept
	P*	0.561	Reject
	S	0.555	Accept
	W	0.554	Accept
	Y	0.547	Accept
	U	0.539	Accept
	D*	0.539	Reject
	C*	0.528	Reject
	L*	0.502	Reject
	I*	0.491	Reject
	G*	0.488	Reject
	Q*	0.477	Reject
	O*	0.447	Reject
	N*	0.420	Reject
	A*	0.401	Reject
	K*	0.387	Reject
	V	0.367	Accept
	M*	0.364	Reject
	H*	0.170	Reject

From Table 5 above we see two outliers, P* and V. P* was rejected when four proposals scoring below it were accepted. V was accepted although it ranked third from the bottom. By taking a closer look at these two proposals, we look to gain insight into the nature of such occurrences.

Table 6: Anomaly Investigation

Value Name	Weighted Contribution to Value Function P* (rejected)	V (accepted)
Tenets Impacted	0.042	0.028
Gap Impact	0.039	0.000
Classification	0.042	0.042
Time to Counter	0.112	0.021
Technical Performance	0.028	0.055
Suitability	0.042	0.056
Interoperability	0.046	0.0455
Technical Risk	0.033	0.011
Fielding Timeline	0.045	0.027
Operations Burden	0.055	0.034
Work Load	0.070	0.005
Training Time	0.000	0.035
Program Maturity	0.008	0.008
Total Score	0.561	0.367

Key	
Value contribution	**Color Identifier**
Top third	
Middle third	
Bottom third	
*	rejected proposal

Both proposal P* and proposal V are presented in Table 6: Anomaly Investigation. All 13 values are listed to provide information as to how well each proposal scored for each category. The value contribution to the total score is coded using a green-yellow-red metric. Proposals that possess highly valuable characteristics are shaded green, mildly valuable are yellow, and minimally valuable in red. For example, Gap Impact contains 9 different measures: G1, G2, G3, G4, G5, G6, G7, G8, and none, where G1 is considered the most desired category and is ranked first. If a proposal meets a Gap Impact at the G1-G3 level, it receives the green shading. Conversely, if it falls between G7 – none, it receives the red shading. This metric thus reveals that both proposal P* and V scored poorly for Gap Impact.

When compared to proposal V (accepted), proposal P* actually scores better in the following areas: Tenets Impacted, Time to Counter, Technical Risk, Fielding Timeline, Operations Burden, and Work Load. However, proposal P* scores poorly for

Training Time (0.000) as compared to proposal V (0.035). This observation may be the reason for JIEDDO's decision to reject the proposal. However, it still leaves us wondering why such a low scoring proposal like proposal V would be accepted as it does not meet any of the desired Gap Impact requirements.

From these observations, we are able to make the following conclusions. First, the value model appears valid for non-R&D proposals. However, it is necessary to check the sensitivity of the proposals to simultaneous weight changes. Conducting sensitivity analysis may explain why Proposal P* was rejected. Second, implementing a value model to aid the decision making process is necessary for making consistent and justifiable decisions. The decision to accept proposal V is inconsistent with previous JIEDDO decisions.

IV.C Sensitivity Analysis

Sensitivity analysis is conducted based on the ranking assessment technique outlined in chapter three. The minimum distance matrix was produced based on the L_2 norm calculation. Additionally, the distance matrix produced via the optimization technique was utilized to construct the similarity matrix for this problem. Both the distance and similarity matrix for the thirty JIEDDO proposals under evaluation are provided in Appendix A.

The author conducts Factor Analysis on the similarity matrix in order to investigate possible clustering among proposals. Clustering among proposals indicates observed commonalities among proposals. Utilizing the heuristic outlined by Dillon and Goldstein, the author identified three clusters.

Table 7: 3 Factor Analysis (Rotated)

Proposal Ranked	Factor 1	Factor 2	Factor 3	Score
1	0.358	-0.461	0.711	0.822
2	0.439	-0.300	0.849	0.727
3*	0.500	-0.435	0.716	0.683
4	0.522	-0.377	0.746	0.672
5*	0.521	-0.443	0.701	0.672
6	0.598	-0.459	0.636	0.620
7	0.718	-0.350	0.587	0.613
8*	0.669	-0.496	0.523	0.599
9	0.743	-0.414	0.517	0.584
10	0.681	-0.521	0.491	0.576
11	0.668	-0.515	0.525	0.565
12	0.693	-0.504	0.492	0.563
13*	0.770	-0.459	0.446	0.561
14	0.692	-0.531	0.473	0.561
15	0.746	-0.479	0.439	0.555
16	0.686	-0.524	0.484	0.554
17	0.732	-0.491	0.459	0.539
18*	0.687	-0.541	0.461	0.539
19*	0.670	-0.557	0.463	0.528
20*	0.630	-0.629	0.422	0.502
21*	0.597	-0.636	0.460	0.491
22*	0.623	-0.619	0.443	0.488
23*	0.584	-0.653	0.435	0.477
24*	0.518	-0.703	0.441	0.447
25*	0.488	-0.740	0.457	0.420
26*	0.484	-0.807	0.317	0.401
27*	0.452	-0.827	0.305	0.387
28	0.447	-0.804	0.329	0.367
29*	0.435	-0.868	0.252	0.364
30*	0.159	-0.800	0.476	0.170
Varimax	10.772	10.235	8.095	
Proportional variance explained	36%	34%	27%	
Cumulative variance explained	36%	70%	97%	

* indicates rejected proposal

Based on these findings, the following observations are made: The first cluster, one whose proposals produced the largest value model scores among the thirty proposals, would be recommended to JIEDDO for acceptance. Given JIEDDO's risk tolerance, one could determine whether it is appropriate it accept the second cluster of proposals or reject them or take a closer look at the members of this group. The third cluster, those with which proposals scored among the lowest using the value model, should be rejected. Thus, we would have the tolerance boundaries based on those provided in Table 8.

Table 8: 3 Factor Analysis (Rotated w/Tolerance Boundaries)

Proposal Ranked	Factor 1	Factor 2	Factor 3	Score
1	0.358	-0.461	0.711	0.822
2	0.439	-0.300	0.849	0.727
3*	0.500	-0.435	0.716	0.683
4	0.522	-0.377	0.746	0.672
5*	0.521	-0.443	0.701	0.672
6	0.598	-0.459	0.636	0.620
7	0.718	-0.350	0.587	0.613
8*	0.669	-0.496	0.523	0.599
9	0.743	-0.414	0.517	0.584
10	0.681	-0.521	0.491	0.576
11	0.668	-0.515	0.525	0.565
12	0.693	-0.504	0.492	0.563
13*	0.770	-0.459	0.446	0.561
14	0.692	-0.531	0.473	0.561
15	0.746	-0.479	0.439	0.555
16	0.686	-0.524	0.484	0.554
17	0.732	-0.491	0.459	0.539
18*	0.687	-0.541	0.461	0.539
19*	0.670	-0.557	0.463	0.528
20*	0.630	-0.629	0.422	0.502
21*	0.597	-0.636	0.460	0.491
22*	0.623	-0.619	0.443	0.488
23*	0.584	-0.653	0.435	0.477
24*	0.518	-0.703	0.441	0.447
25*	0.488	-0.740	0.457	0.420
26*	0.484	-0.807	0.317	0.401
27*	0.452	-0.827	0.305	0.387
28	0.447	-0.804	0.329	0.367
29*	0.435	-0.868	0.252	0.364
30*	0.159	-0.800	0.476	0.170
Varimax	10.772	10.235	8.095	
Proportional variance explained	36%	34%	27%	
Cumulative variance explained	36%	70%	97%	

* indicates rejected proposal

For an organization that is risk averse, proposals below the black line would be rejected by JIEDDO. This would indicate a reject rate of approximately 83.3%. From the table above, we notice that the majority of rejected proposals fall at or below that of proposal 18. Based on the value model results and the above factor analysis, this indicates that JIEDDO's risk tolerance level may be lower than that indicated by the black line in

Table 8 above. Lowering the acceptance boundary to include those proposals above that of proposal 18 appears problematic because the boundary cuts right threw the cluster of proposal 6 through proposal 20. Specifically, the author acknowledges that proposal 20 through proposal 22 borders Factor one and Factor two. As such, for an organization that is more risk tolerant, it is appropriate to extend the acceptance line to those proposals sitting above the red line.

Further insight is gained after conducting cluster analysis on the set.

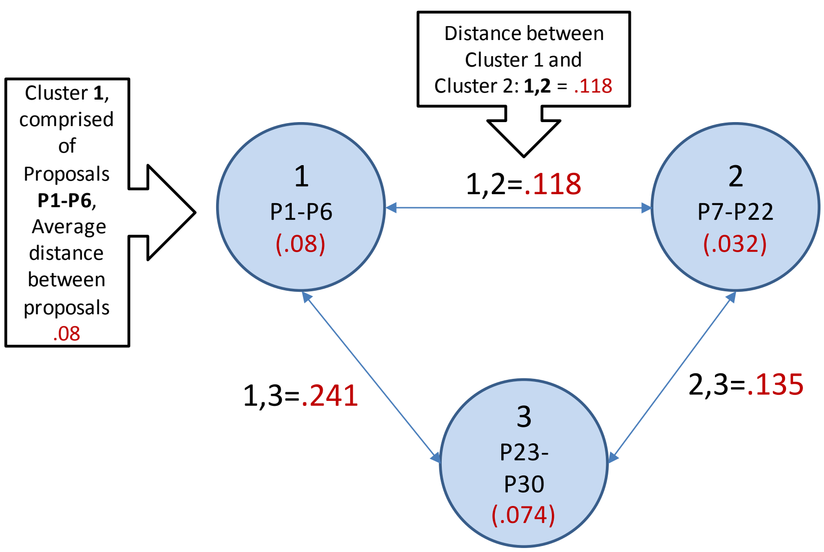


Figure 15: 3 Factor Cluster Analysis

The average distance in the weight space between proposals within a cluster is smaller than those seen between the clusters themselves. From Figure 15, we see that the second cluster contains the tightest proposals; proposal 7 through proposal 22 are on average, a distance of 0.032 from one another. Both clusters one and three contain proposals that are on average approximately 0.080 and 0.074 away from each other, respectively. The expectation of the cluster containing the highest scoring proposals to fall the farthest from that of the lowest scoring proposals is demonstrated here. Cluster one is an average distance of 0.241 from cluster three. Cluster one and two are the most near with an average distance of 0.118. Finally, we see that cluster two and cluster three are approximately 0.135 from one another.

Seeking to reduce the number of rotated factors, this analysis was repeated for two retained factors and is shown in the tables below.

Table 9

Proposal Ranked	Factor 1	Factor 2	Score
1	0.732	-0.477	0.822
2	0.902	-0.327	0.727
3*	0.831	-0.479	0.683
4	0.872	-0.424	0.672
5*	0.832	-0.492	0.672
6	0.832	-0.526	0.620
7	0.882	-0.446	0.613
8*	0.790	-0.583	0.599
9	0.840	-0.518	0.584
10	0.771	-0.612	0.576
11	0.789	-0.601	0.565
12	0.781	-0.597	0.563
13*	0.801	-0.571	0.561
14	0.764	-0.625	0.561
15	0.777	-0.586	0.555
16	0.769	-0.616	0.554
17	0.782	-0.595	0.539
18*	0.751	-0.635	0.539
19*	0.740	-0.646	0.528
20*	0.677	-0.712	0.502
21*	0.684	-0.710	0.491
22*	0.689	-0.700	0.488
23*	0.655	-0.726	0.477
24*	0.612	-0.762	0.447
25*	0.602	-0.791	0.420
26*	0.489	-0.864	0.401
27*	0.457	-0.879	0.387
28	0.474	-0.853	0.367
29*	0.402	-0.919	0.364
30*	0.397	-0.785	0.170
Varimax	15.822	12.718	
Proportional variance explained	53%	42%	
Cumulative variance explained	53%	95%	

Table 10

Proposal Ranked	Factor 1	Factor 2	Score
1	0.732	-0.477	0.822
2	0.902	-0.327	0.727
3*	0.831	-0.479	0.683
4	0.872	-0.424	0.672
5*	0.832	-0.492	0.672
6	0.832	-0.526	0.620
7	0.882	-0.446	0.613
8*	0.790	-0.583	0.599
9	0.840	-0.518	0.584
10	0.771	-0.612	0.576
11	0.789	-0.601	0.565
12	0.781	-0.597	0.563
13*	0.801	-0.571	0.561
14	0.764	-0.625	0.561
15	0.777	-0.586	0.555
16	0.769	-0.616	0.554
17	0.782	-0.595	0.539
18*	0.751	-0.635	0.539
19*	0.740	-0.646	0.528
20*	0.677	-0.712	0.502
21*	0.684	-0.710	0.491
22*	0.689	-0.700	0.488
23*	0.655	-0.726	0.477
24*	0.612	-0.762	0.447
25*	0.602	-0.791	0.420
26*	0.489	-0.864	0.401
27*	0.457	-0.879	0.387
28	0.474	-0.853	0.367
29*	0.402	-0.919	0.364
30*	0.397	-0.785	0.170
Varimax	15.822	12.718	
Proportional variance explained	53%	42%	
Cumulative variance explained	53%	95%	

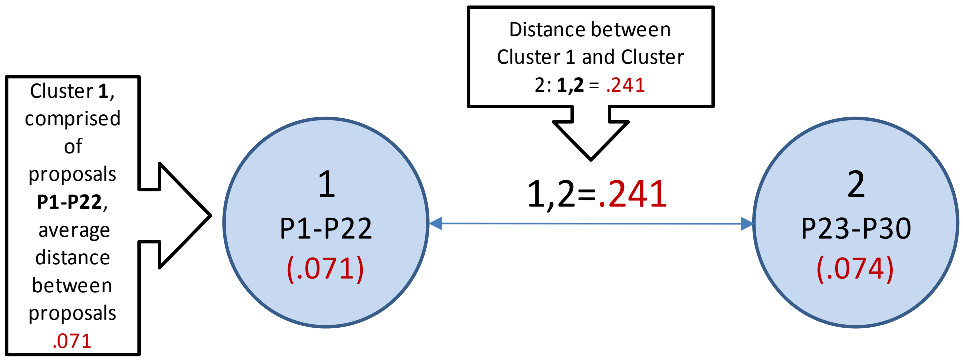


Figure 16: 2 Factor Cluster Analysis

The two-factor analysis produced similar results as those seen for the three-factor cluster analysis. Cluster one above contains the combined proposals found in clusters one and two shown in Figure 15: 3 Factor Cluster Analysis, proposal 1 through proposal 22. Cluster two above is analogous that that of the third cluster in the three factor cluster analysis. From the above, we see that cluster one contains proposals that are an average of 0.071 from each other within the cluster. Similarly, cluster two contains proposals that are 0.074 from one another. While each cluster one and cluster two exhibit similar characteristics within the clusters themselves, we recognize that the distance between the two groupings themselves is relatively far, 0.241. This large distance implies that there exists a distinct difference between those proposals that comprise each group.

Recognizing that the presence of the R&D proposals within the factor analysis may affect the clusters, it is important to investigate which of the 25 proposals load on the new factors. Rotated factor analysis was conducted on the new set of 25 proposals.

When three factors were retained, all of the proposals loaded on the first two factors. As a result, the two rotated factor analysis is provided in Table 11.

Table 11: Rotated Factor Analysis (Reduced Set)

Proposal Ranked	Factor 1	Factor 2	Score
2	0.880	0.330	0.727
4	0.848	0.429	0.672
6	0.826	0.519	0.620
7	0.896	0.419	0.613
10	0.805	0.577	0.576
11	0.803	0.580	0.565
12	0.805	0.569	0.563
13*	0.828	0.538	0.561
14	0.787	0.599	0.561
15	0.817	0.545	0.555
16	0.795	0.588	0.554
17	0.815	0.560	0.539
18*	0.778	0.605	0.539
19*	0.769	0.617	0.528
20*	0.711	0.682	0.502
21*	0.708	0.687	0.491
22*	0.721	0.671	0.488
23*	0.677	0.706	0.477
24*	0.627	0.749	0.447
25*	0.622	0.777	0.420
26*	0.504	0.857	0.401
27*	0.484	0.865	0.387
28	0.490	0.846	0.367
29*	0.406	0.922	0.364
30*	0.395	0.795	0.170
Eigen values	13.198	10.810	
Proportional variance	53%	43%	
Cumulative variance	53%	96%	

The reduced set contains 25 proposals verses, the original 30. From the table above we see that our boundary is set at proposal 22* for this new data set. This observed boundary location is the same as that which was set for the rotated three-factor analysis. As such, we suggest that proposals that fall at or above that of proposal 22* exhibit similar patterns in behavior. There are 17 proposals that rank at or above that identified by proposal 22*. Proposals 23* through 30* comprise the remaining eight proposals. We would expect the top ranked alternatives, the first 17, to be accepted. This analysis supports the rejection of proposals falling below proposal 22*.

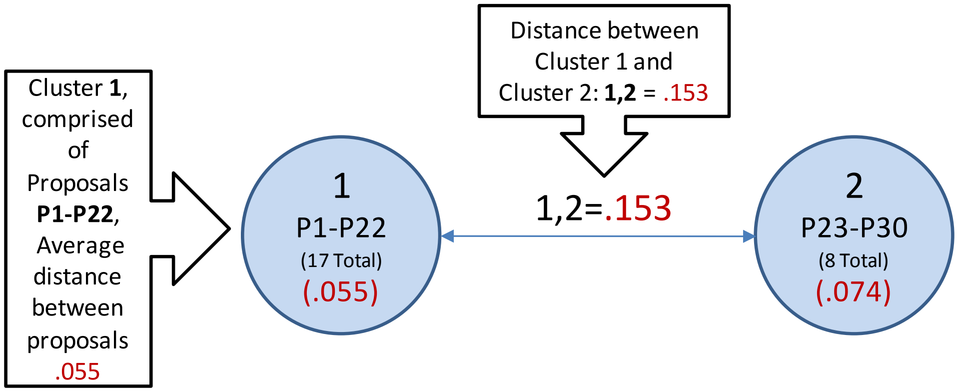


Figure 17: 2 Factor Cluster Analysis for Reduced Set

The patterns exhibited in Figure 17 above nearly mirror those seen for the two-factor cluster analysis conducted on all 30 proposals. However, the distinction between the full and reduced set is captured in the first cluster. The distances between proposals within this set are approximately 0.055, while those seen for the second cluster are 0.074. While the distance between the two clusters in the original set was approximately 0.241, the average distance between the two clusters for the reduced set is smaller, 0.153.

In addition to observing the clustering affect among proposals, it is important to investigate the weight changes themselves to provide a more extensive comparison of the proposals. All of the weights that comprise each cell of the distance matrix were recorded for their respective proposal. From these weight values, it was possible to record the percent weight change that occurred from the original global weight to the new weight that minimized the L_2 norm for this specific problem. The images provided depicts the percent weight change as well as the actual weight changes that occurred among proposals that ranked among the highest in the set.

The first set of two figures describes the percent and actual weight changes for the first proposal. The images show the weights sorted from the largest original global weight value (Gap Impact) to the least original global weight value (Program Maturity) for both percent change and actual weight change images.

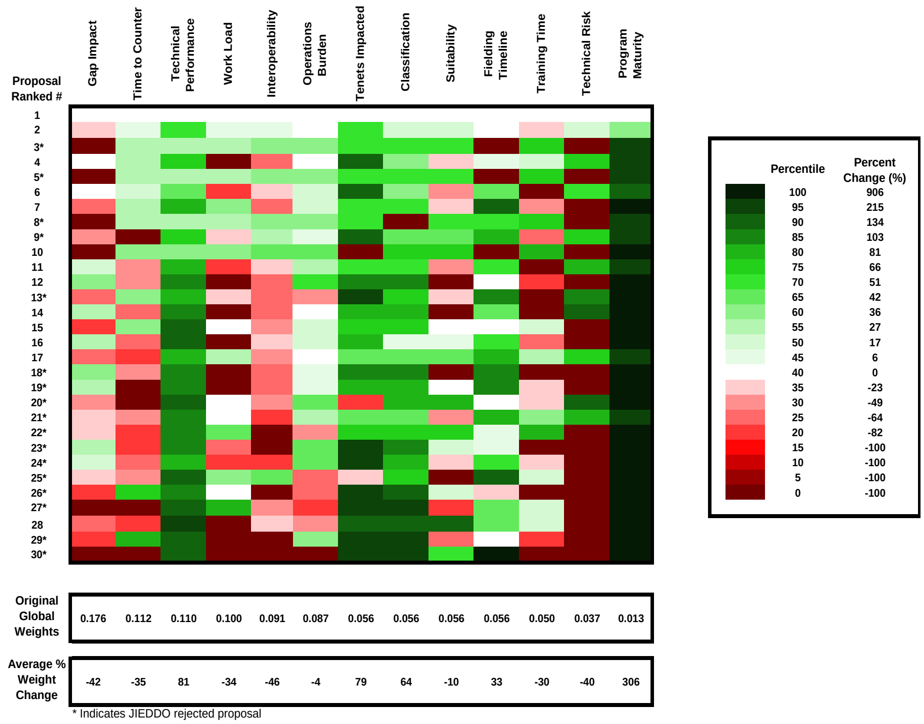


Figure 18: Proposal #1 Percent Change

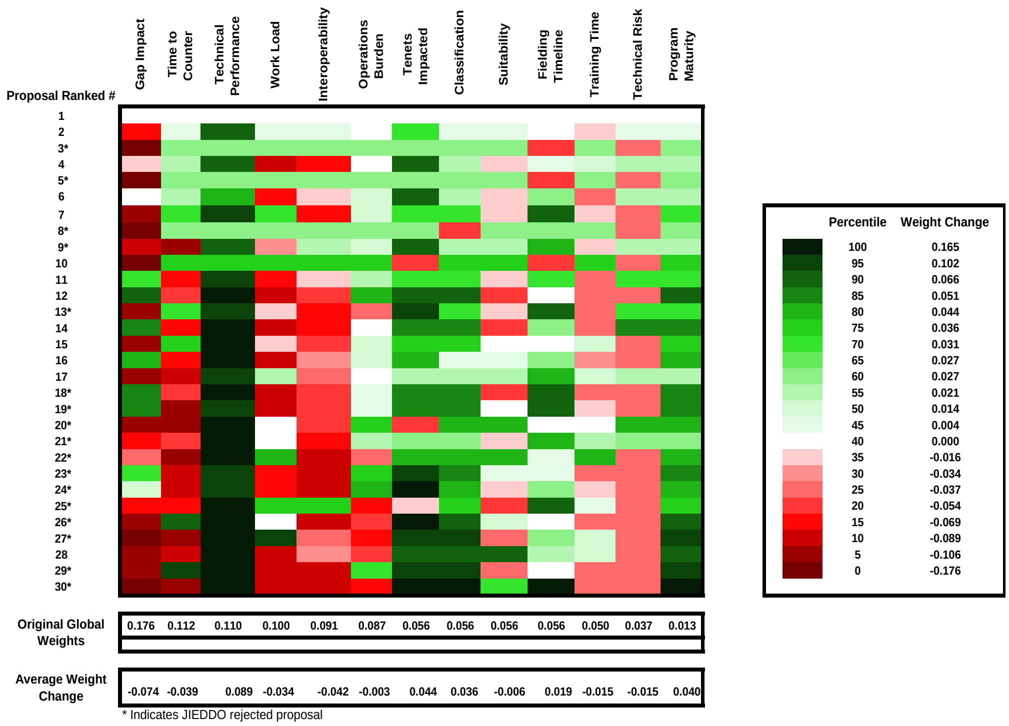


Figure 19: Proposal #1 Weight Change

Figure 19 illustrates that the average weight change across all 30 proposals for Gap Impact is -0.074, while the average weight change for Program Maturity is 0.040. Sorting the data by average weight change, from most positive to most negative, for each of the thirteen values, allows us to see which value, on average, changes the most. Additionally the "Sorted Vertically" metrics describe the same set of information as those mentioned above; however, the data has been sorted by the average weight change for each value.

We see from the average weight change images shown in Figure 20 and Figure 21 that Program Maturity, Technical Performance, Tenets Impacted, and Classification need to increase simultaneously in order for some rank order pressure to affect that of the top ranked alternative. Meanwhile, the weight for Gap Impact needs to decrease. This indicates that proposal one scored very well in meeting the Gap Impact, and relatively poor for Program Maturity, Technical Performance, Tenets Impacted, as well as Classification.

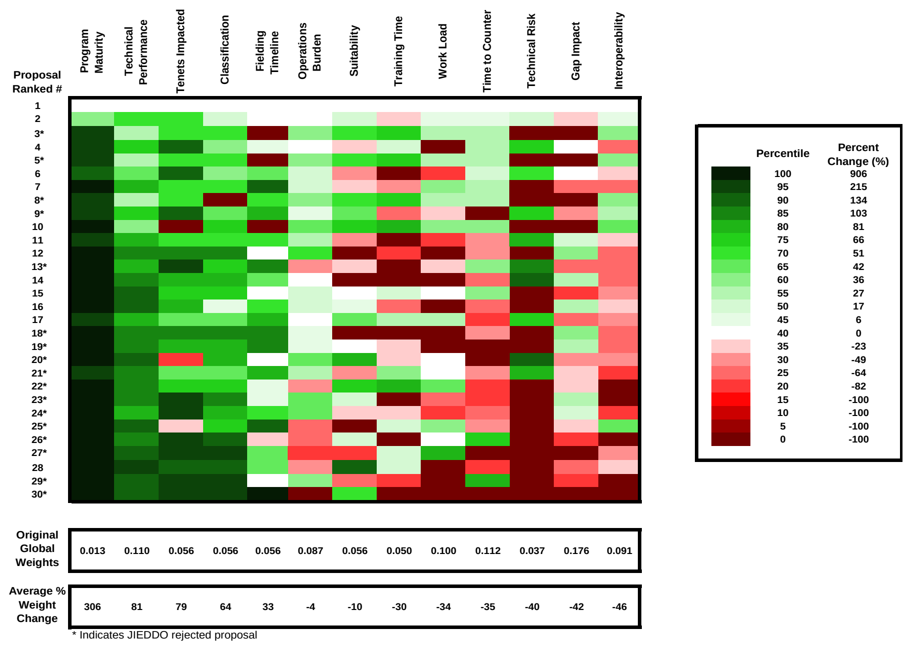


Figure 20: Proposal #1 Percent Change (Sorted Vertically)

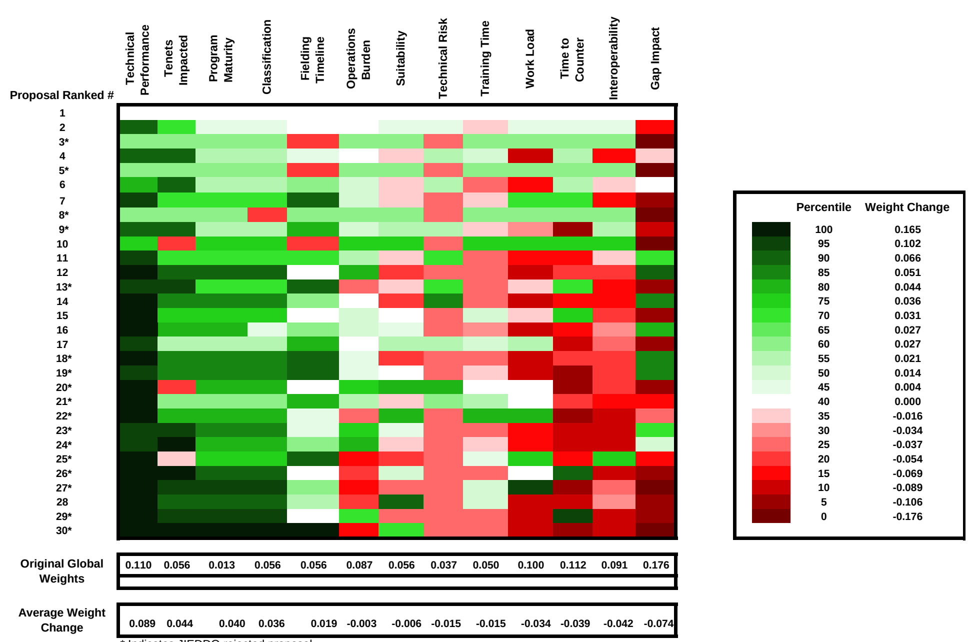


Figure 21: Proposal #1 Weight Change (Sorted Vertically)

We expect that significant weight changes need to occur for a rank reversal to occur among proposals that scored among the highest and lowest for this evaluation. This suspicion is supported by the previously produced images. We see that the red and green suggests both significant weight increases and decreases for rank changes to occur. This phenomenon is observed for all proposals in the proposal one example. That is, as the distance between proposals increases, the ability for a rank change to occur is dependent on larger positive or negative simultaneous weight changes. All of the images generated for this percent weight change analysis are provided in Appendix C.

A more interesting area of interest is those proposals that fall in the mid-range for JIEDDO proposals. From this, the following question surfaces. Given that we know proposals that score highly should be accepted, what conclusions could be drawn from those that score in the second and third clusters for value scoring? To examine this further, we extract percent change images for two proposals that line in this mid range. We begin with analysis for the previously evaluated Proposal P*, the 13th ranked proposal.

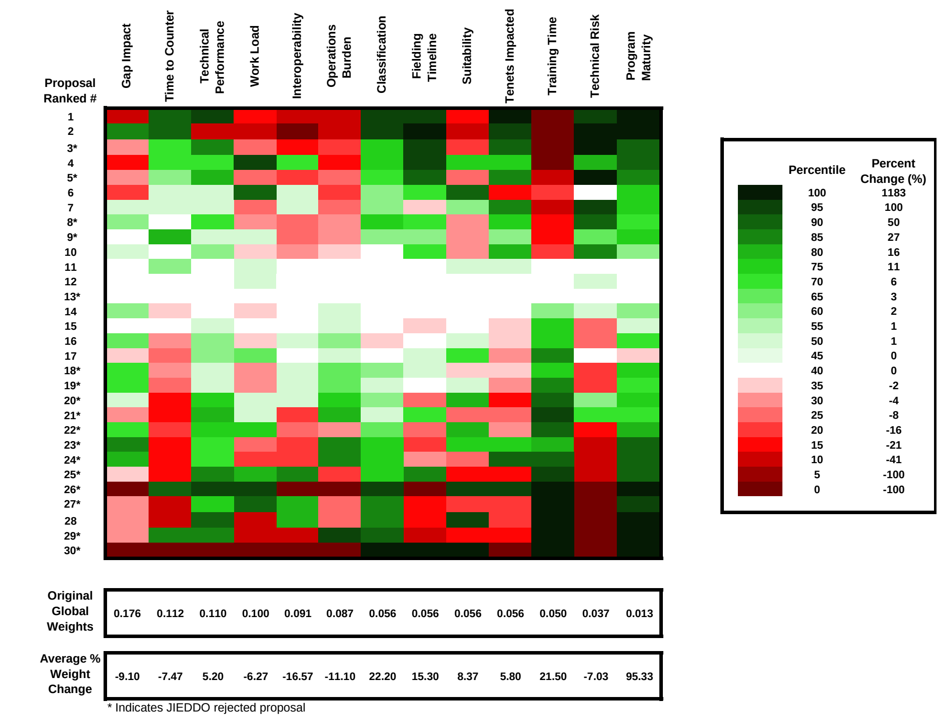


Figure 22: Proposal #13 Percent Change

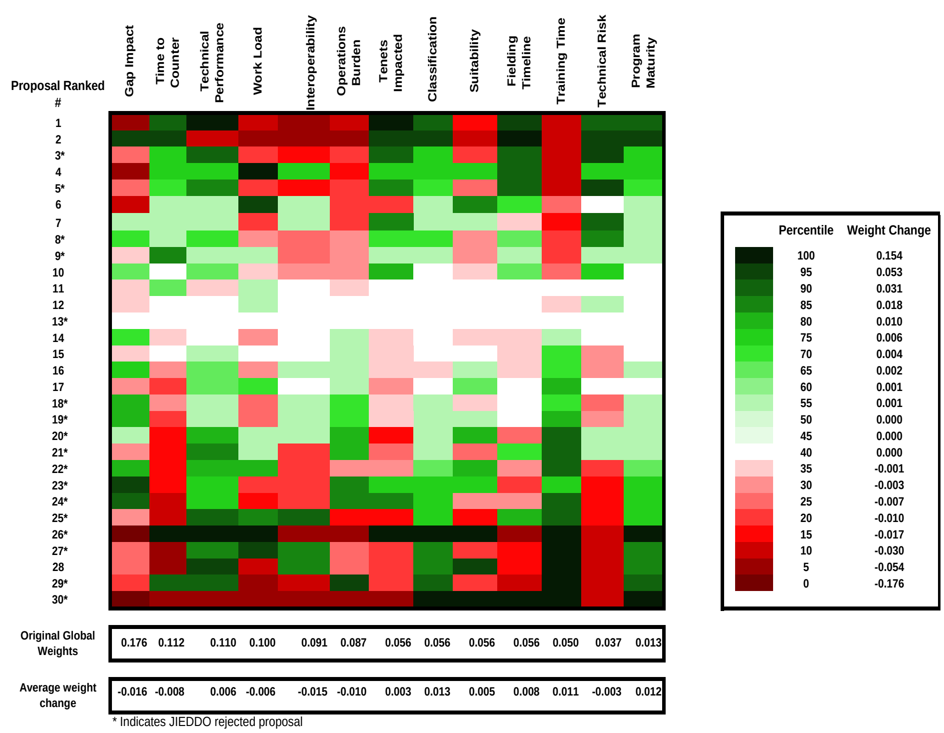


Figure 23: Proposal #13 Weight Change

From the images of proposal 13, we see a light band of color between proposals 11 to 14 with some mild shading that occurs just beyond that region. In both of the transformed images shown below, we observe the sensitivity of small percent (or actual weight) changes to rank change. The percent change in this band is observed to lie between one and negative two percent. This amounts to an actual weight change of +/- .0001. We see the potential for inconsistency in choosing to reject a proposal like 13, whose immediate neighbors 12 and 14, were accepted. Minimal if no changes are required among the values for rank changes to occur.

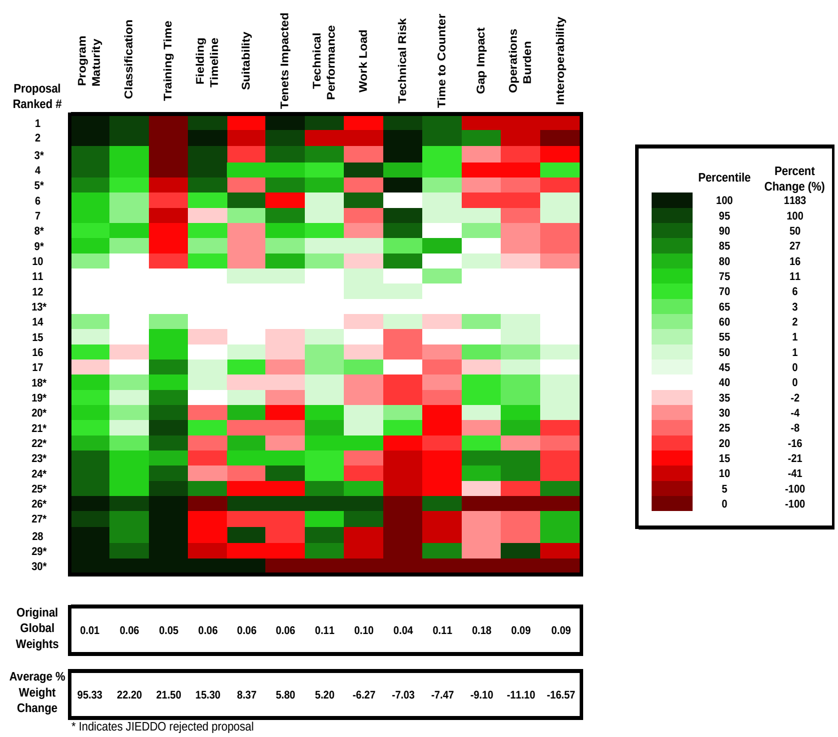


Figure 24: Proposal #13 Percent Change (Sorted Vertically)

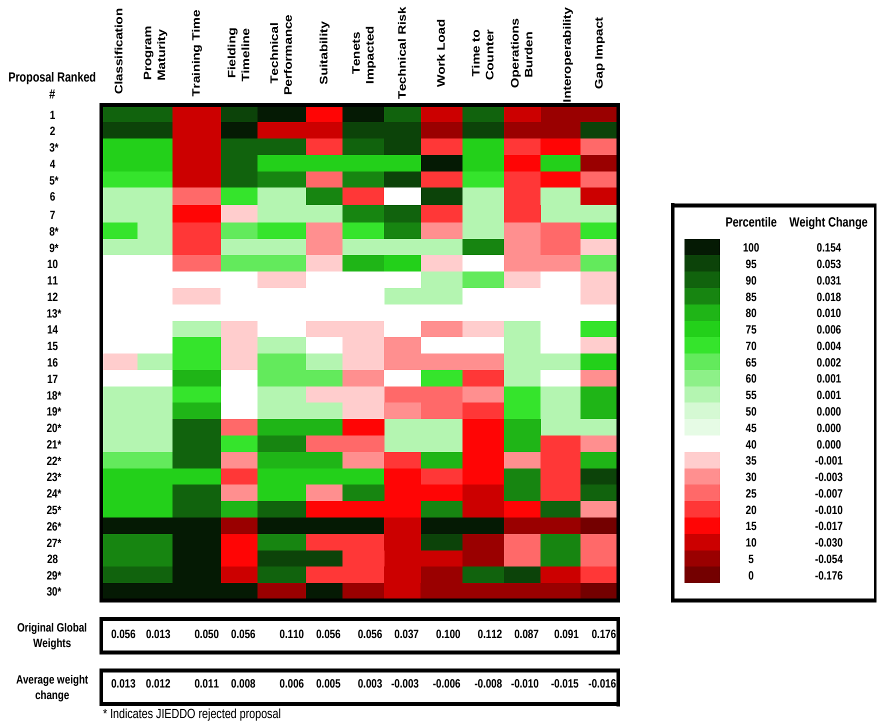
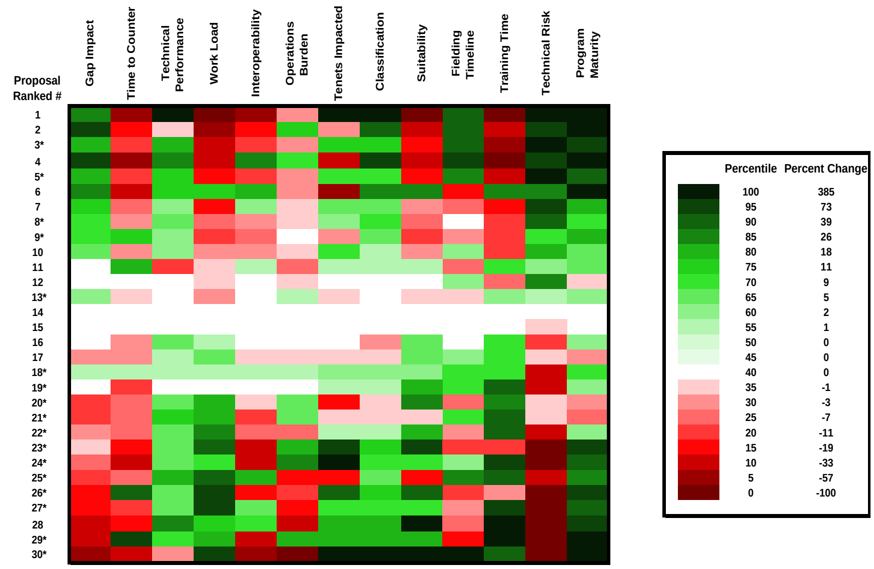


Figure 25: Proposal #13 Weight Change (Sorted Vertically)

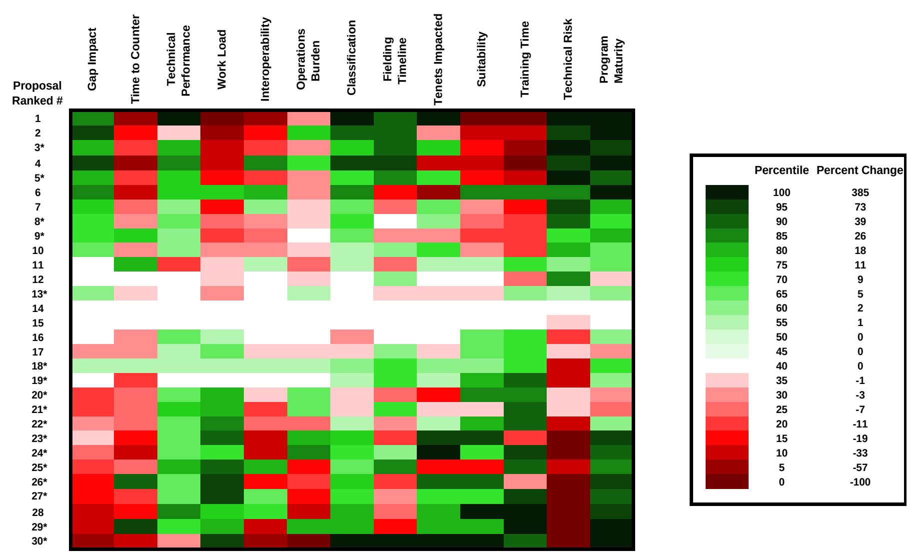
Continuing this investigation, we see the same shading ban appear for proposal 13's neighbor. We see from the percent change and weight change metric, that proposal 14 scored relatively well for Gap Impact, Technical Performance, Classification, Fielding Timeline, Technical Risk, and Program Maturity. However, indications of poor ratings arise for Time to Counter, Work Load, Interoperability, Suitability Level, as well as Training Timeline. These patterns are exhibited in Figure 26 through Figure 29.



	Gap Impact	Time to Counter	Technical Performance	Work Load	Interoperability	Operations Burden	Tenets Impacted	Classification	Suitability	Fielding Timeline	Training Time	Technical Risk	Program Maturity
Original Global Weights	0.176	0.112	0.110	0.100	0.091	0.087	0.056	0.056	0.056	0.056	0.05	0.037	0.013
Average % Weight Change	-3.800	-11.133	7.867	0.500	-10.633	-5.033	6.867	12.167	6.267	9.133	3.967	-11.900	52.667

* Indicates JIEDDO rejected proposal

Figure 26: Proposal #14 Percent Change



	Gap Impact	Time to Counter	Technical Performance	Work Load	Interoperability	Operations Burden	Classification	Fielding Timeline	Tenets Impacted	Suitability	Training Time	Technical Risk	Program Maturity
Original Global Weights	0.176	0.112	0.110	0.100	0.091	0.087	0.056	0.056	0.056	0.056	0.05	0.037	0.013
Average % Weight Change	-4	-11	8	1	-11	-5	12	9	7	6	4	-12	53

* Indicates JIEDDO rejected proposal

Figure 27: Proposal #14 Weight Change

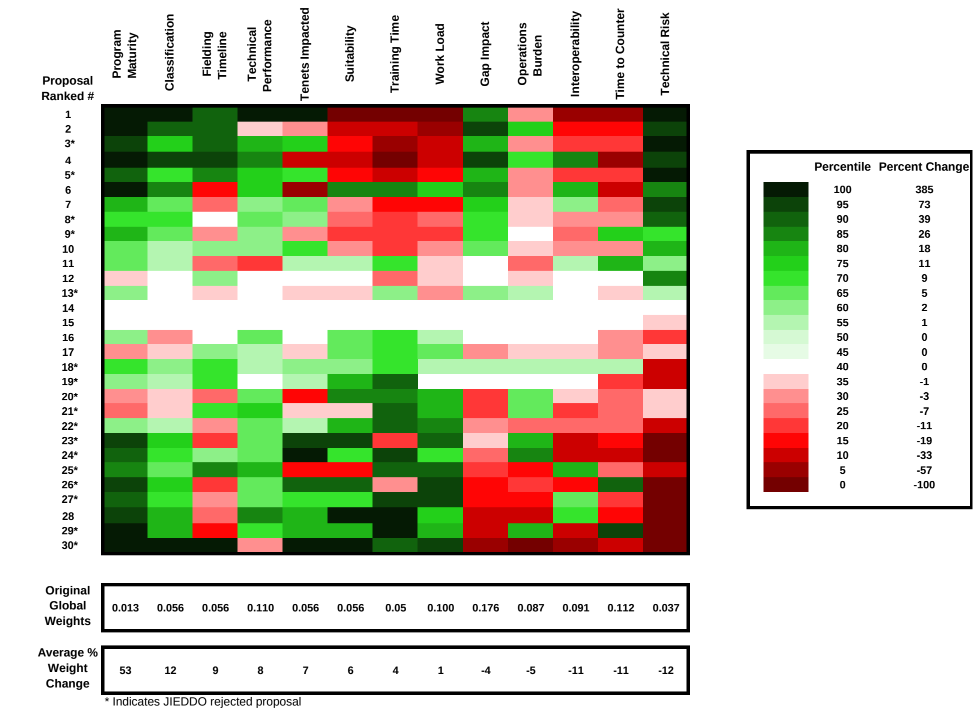


Figure 28: Proposal #14 Percent Change (Sorted Vertically)

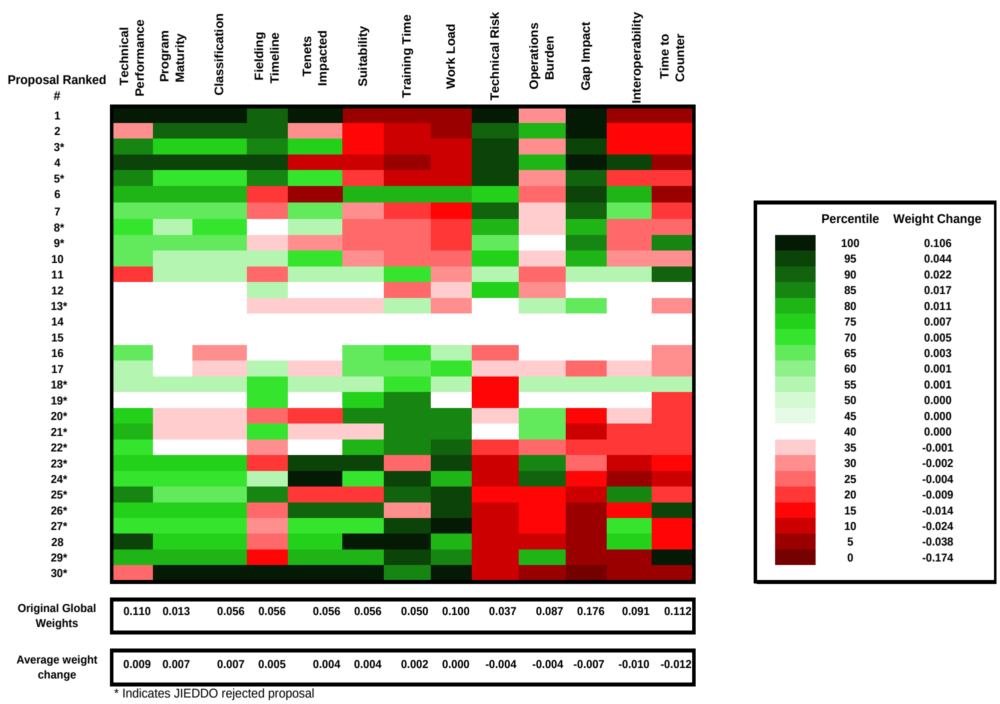


Figure 29: Proposal #14 Weight Change (Sorted Vertically)

Now that we have made observations of the sensitivity of the top two thirds of the provided JIEDDO proposals, it is necessary to turn to the bottom third. For completeness sake, one proposal will be selected as a representative of the set, for discussion. The expected observations for this set would resemble those observed among proposals in the top third. More specifically, we would expect to see significant positive and negative weight changes (as indicated by the green and red shading intensity) in order for a proposal that is ranked relatively low to swap places with one of its competitors. Proposal 26 was randomly selected among the group for observation.

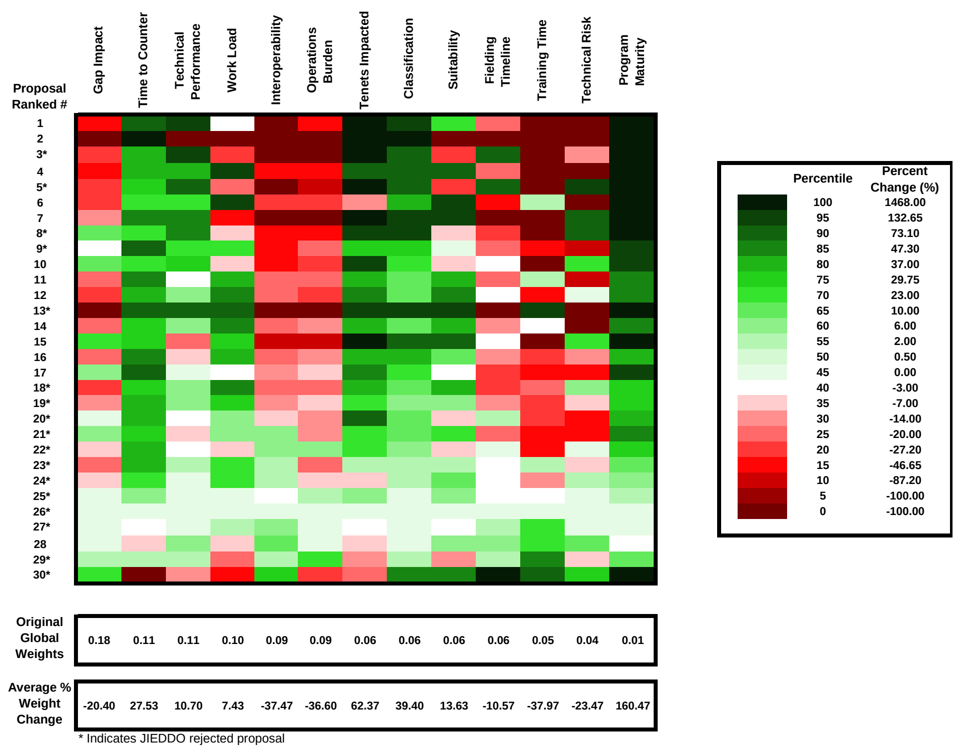


Figure 30: Proposal #26 Percent Change

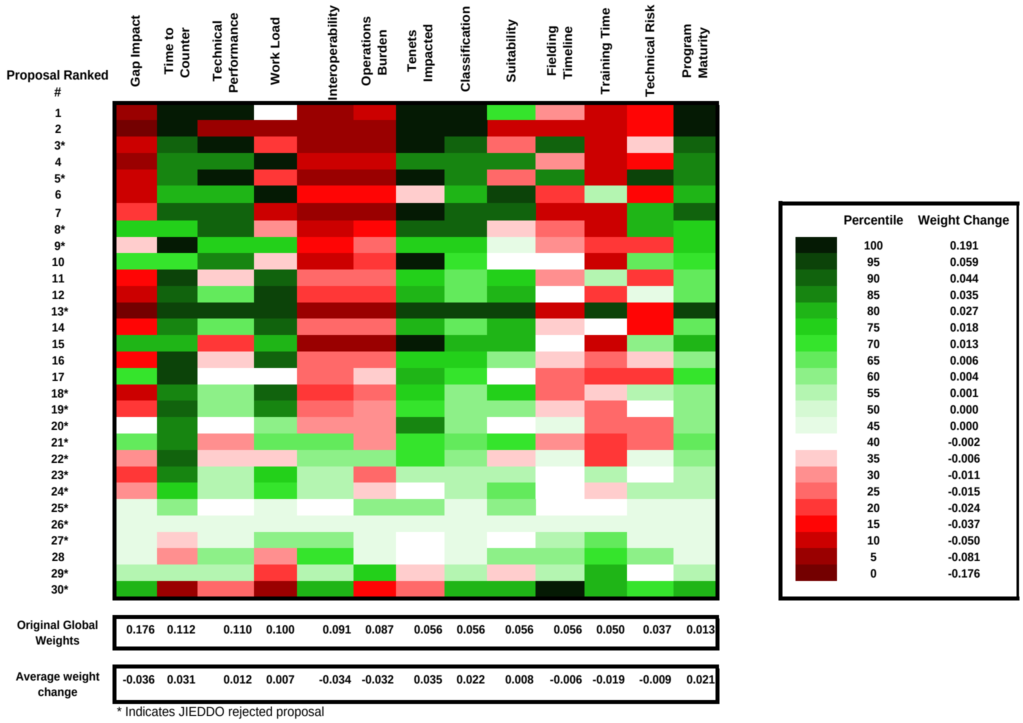


Figure 31: Proposal #26 Weight Change

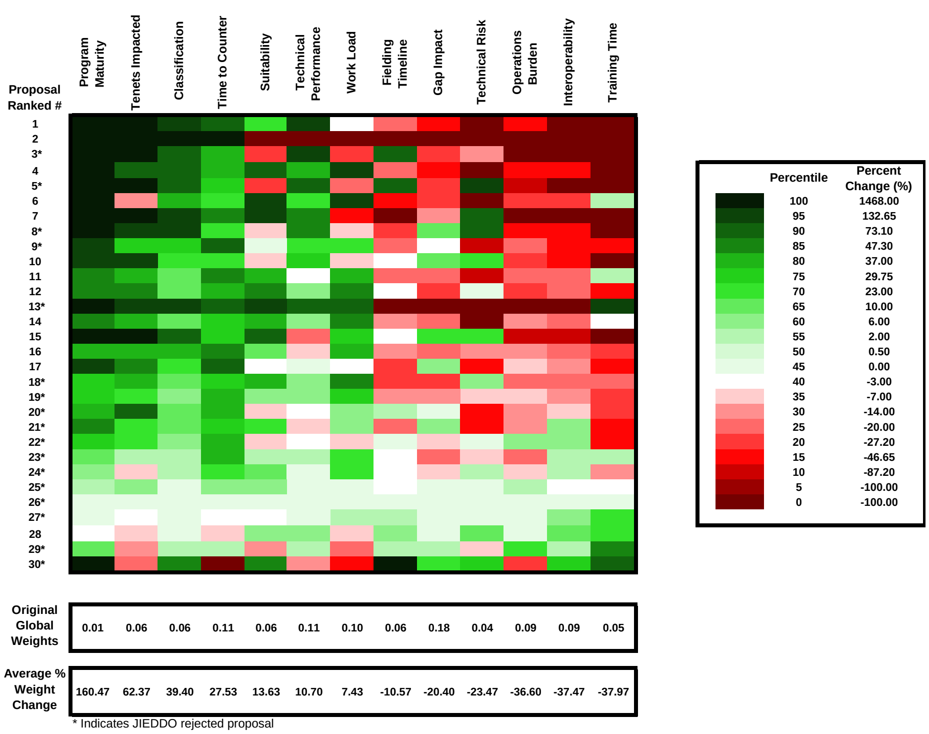


Figure 32: Proposal # 26 Percent Change

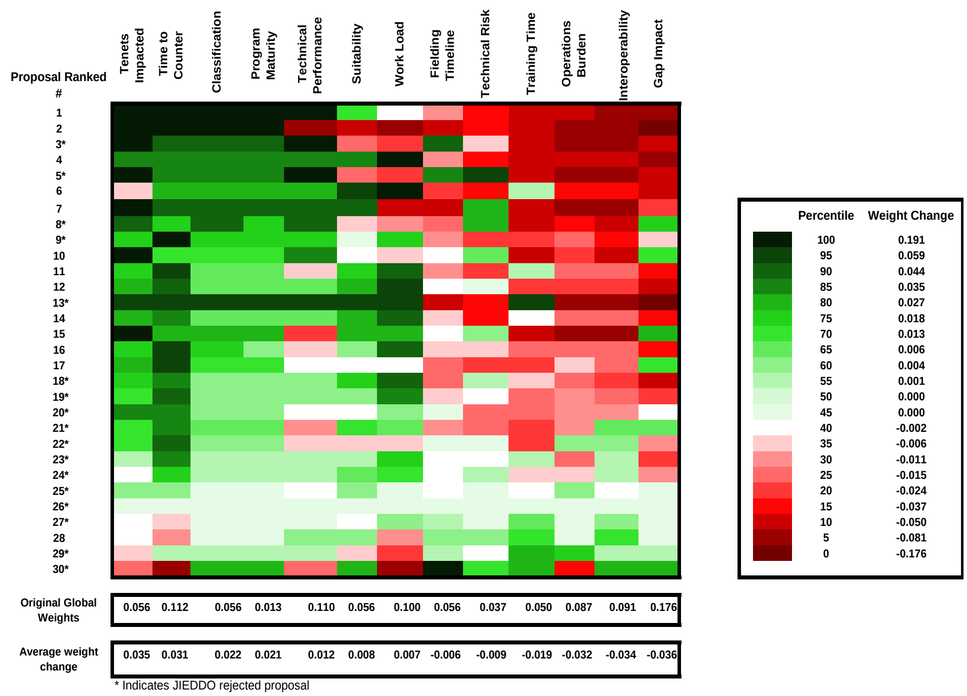


Figure 33: Proposal #26 Weight Change

As predicted, we see intense positive (green) and negative (red) shading in the figures above. The new weights produced from the optimization problem suggest simultaneously increasing the values for Tenets Impacted, Time to Counter, and Program Maturity. Conversely, we see weight decreases for Training Time, Operations Burden, Interoperability, and Gap Impact. Technical Performance, Suitability, Work Load, Fielding Timeline, and Technical Risk show indications of positive and negative changes as proposals comparisons are made between proposal 26 and the highest ranked proposals.

IV.E Summary

The purpose of this chapter is to provide a clear and concise summary of the JIEDDO model validation process as well as the sensitivity analysis procedures thereof. From this result, this research proposed a method for evaluating proposals using discriminant analysis. More specifically, given 13 distinct considerations (values) and a known accept or reject outcome, we were able to develop a technique that mirrors JIEDDO's decision process. Given a new set of proposals, we would be able to accurately predict whether a panel of decision makers is likely to accept or reject the proposal. Once this insight was gained, the second part of the chapter was dedicated to the sensitivity of the JIEDDO value model global weights within the decision problem. From this, the research proposed a new sensitivity analysis imaging technique utilizing known math programming and multivariate techniques.

V. Conclusions and Recommendations

V.A. Introduction

Military members serving in Iraq and Afghanistan face many challenges as they persist in their counter terrorism mission. Insurgents are undoubtedly dedicated to using unconventional means, particularly IEDs, to defeat the Allied coalition. We have seen military members serving in Iraq and Afghanistan, in particular, require a great deal of support from both the Department of Defense as well as the American people as they continue to face and overcome obstacles. In response to this need, JIEDDO has served as a lead organization in the solicitation and development of C-IED projects. Their primary motivation is centered on answering the warfighter's urgent need by delivering the most appropriate C-IED systems as rapidly as possible.

We have seen how Decision Analysis has the potential to serve JIEDDO in critically evaluating and selecting C-IED proposals. The development of a Value Focused Thinking model that properly identifies JIEDDO values as a basis for proposal evaluation will serve as an appropriate mechanism for evaluating the organization's ability to meet the warfighters perceived needs. The criticality of verifying and validating the JIEDDO value model's robustness is imminent in cases where lives are at stake.

V.B. Research Contributions

The purpose of this research was to provide contributions to the field of Decision Analysis in the areas of model validation and sensitivity analysis. This research showed how Decision Analysis and Discriminant Analysis techniques can be merged to provide insight into decision outcome.

The first contribution is in the area of model validation. This research applied Discriminant Analysis techniques to the model as a means to develop a function that describes a particular decision process. As such, this research showed, by means of the Lachenbruch Holdout Procedure, that it is possible to utilize value model attributes to form a discriminant function to describe the proposal evaluation process. This procedure is useful when utilizing value focused thinking models, like JIEDDO, to repeatedly make a decision.

The second contribution to the field of DA is in the area of boundary determination. For decision models where multiple alternatives are selected, it is important to identify at what point should the line be drawn for selecting a given alternative verses rejecting it. Factor Analysis serves as a useful technique for determining the acceptance-rejection boundary. The correlation between proposals in the factors themselves allows us to identify clusters of proposals that are considered very similar. As a result, those proposals that are clustered are considered too similar to reject one while accepting the others.

The third contribution to the field of DA is in the area of Sensitivity Analysis. Prior research demonstrated the usefulness of using math programming techniques to determine various distances between alternatives. This research utilized math programming techniques to develop an image profiling tool to evaluate proposals. Applying this technique allows decision makes to understand how well a specific proposal preformed against each one of its competitors.

V.C. Recommendations for Further Research

Sensitivity Analysis remains a trusted mechanism for determining the level of confidence a DM can have in the problem they are looking to solve. Decision Analysts recognize that much of sensitivity analysis involves observations in small or even large fluctuations among the weights themselves. We have seen how the implication of weight uncertainty leads us to pose the following questions, “Are the values weighted appropriately in a manner that truly reflects the decision maker’s preference? If there exists error among the weights, how much or little error is there? How will it affect the decision?” The subjectivity of the weight elicitation process remains at the root of concerns.

However, instead of taking a forward approach to eliciting weights to calculate the value score for a particular decision problem, it would be interesting to investigate a backward approach to extract weights. Given the values and an outcome (i.e. accept or reject as seen in JIEDDO), is it possible to determine the set of weights that would produce such a known outcome? The answer to this question could be approached utilizing discriminant analysis techniques. The idea being simple, using historical data to extract the set of variables and known outcome, it is possible to create a discriminant function that will define each population of interest. This will allow us to determine the weights that a decision maker places on each of the respective value categories. It is then possible to compare the weights produced using this weight extraction procedure to those elicited from the DM. However, the need for access to historical data is imminent for this backward weight extraction to work. This concept will serve beneficial for decision problems whereby a decision is made more than once.

V.D. Conclusions

Decision Analysis models are useful tools for analyzing various alternatives available in order to make the most sound decision for the problem at hand. Value Focused Thinking allows a team of analysts to work with a decision maker to identify the values for the decision, weight the values appropriately, and evaluate alternatives based on the aforementioned criteria. Recognizing that the subjectivity of weight elicitation serves as motivation for model verification and validation, this research demonstrated the practicality and usefulness of applying Discriminant Analysis techniques to verify the consistency between the decision maker's decision and the model's recommendation. Additionally, we recognize the usefulness of checking weight sensitivity via an image profiling technique. Imaging serves as a means for evaluating a given alternative to see how it stands as ranked against its competitors.

The application of such research topics is promising for the JIEDDO proposal evaluation process. There is no question as to the importance of evaluating and selecting the best C-IED proposals to meet the current warfighter's needs. Appropriately developed and validated value models aid decision makers, like JIEDDO, in making decisions that will accommodate our military service members seeking to overcome obstacles in Iraq and Afghanistan.

Appendix

Appendix A: JIEDDO Proposal Data

Alternative	# Tenets	Primary Gap	Classification	Months Useful	Performance	Suitability	Interop. Issues
A*	2	None	FOUO	60	2	4	Significant
B *	0	None	FOUO	60	1	5	None
C*	1	G1	FOUO	12	2	4	Minor
D *	1	G1	FOUO	50	2	3	Minor
E *	1	G6	FOUO	60	1	5	None
F *	1	G6	FOUO	60	1	5	None
G *	1	G6	FOUO	12	3	5	Significant
H*	1	None	FOUO	1	1	4	Significant
I *	1	None	FOUO	36	4	3	Significant
J *	1	None	SEC/REL	60	1	5	None
K *	1	None	FOUO	24	2	3	Minor
L *	0	G8 and Below	FOUO	24	3	5	Minor
M *	1	None	FOUO	60	2	3	Significant
N *	0	None	FOUO	12	4	1	None
O *	3	G3	FOUO	3	2	3	Significant
P *	2	G8 and Below	FOUO	60	2	4	Minor
Q *	2	G2	FOUO	36	2	4	Significant
R	1	G1	FOUO	36	3	3	Minor
S	1	G1	FOUO	50	2	3	Minor
T	1	G1	FOUO	50	2	3	Minor
U	1	None	FOUO	24	3	5	Minor
V	1	None	FOUO	36	3	5	Minor
W	1	None	FOUO	60	3	4	Minor
X	2	G7	SEC/REL	12	2	5	None
Y	1	G1	FOUO	36	3	4	Minor
Z	1	G8 and Below	FOUO	60	2	4	Minor
AA	3	G3	FOUO	60	2	3	Minor
BB	2	G8 and Below	FOUO	60	3	5	None
CC	2	G3	FOUO	60	2	4	Minor
DD	1	G1	FOUO	60	1	5	None

Alternative	TRL	Months to Fielding	% Max Capacity	Interaction Min/Hr	Training Hours	Training Level
A*	2	24	20	2-5	40	3
B *	4	14	0	0-1	0	3
C*	5	8	5	>30	4	3
D *	3	8	5	>30	16	3
E *	1	24	0	0-1	0	3
F *	5	24	0	0-1	0	3
G *	4	18	20	0-1	0	3
H*	1	6	100	16-30	40	3
I *	7	4	1	2-5	1	3
J *	1	9	0	0-1	0	3
K *	2	18	20	0-1	4	3
L *	6	18	1	2-5	4	3
M *	1	24	5	16-30	8	3
N *	3	2	80	0-1	4	3
O *	2	14	1	16-30	8	3
P *	6	6	10	2-5	40	3
Q *	4	20	2	6-15	80	3
R	6	9	2	16-30	24	3
S	6	12	5	>30	20	3
T	4	18	1	16-30	6	3
U	6	4	5	0-1	1	3
V	5	18	20	16-30	4	3
W	4	18	3	2-5	2	3
X	6	6	2	2-5	4	3
Y	5	12	5	16-30	8	3
Z	3	4	2	0-1	4	3
AA	7	7	2	>30	20	3
BB	6	12	2	0-1	4	3
CC	6	12	3	6-15	1	3
DD	6	9	0	0-1	0	3

Appendix B: Distance and Similarity Matrices

Table 12: Distance Matrix for 30 JIEDDO Proposals

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0.000	0.096	0.207	0.101	0.207	0.158	0.199	0.207	0.192	0.224	0.171	0.227	0.218	0.219	0.214	0.203	0.193	0.222	0.220	0.243	0.191	0.210	0.231	0.221	0.203	0.275	0.323	0.290	0.310	0.391
2	0.096	0.000	0.049	0.036	0.036	0.073	0.142	0.143	0.133	0.143	0.102	0.111	0.218	0.117	0.280	0.120	0.170	0.122	0.121	0.223	0.172	0.101	0.133	0.139	0.183	0.474	0.483	0.423	0.333	0.424
3	0.207	0.049	0.000	0.008	0.039	0.033	0.080	0.127	0.068	0.137	0.061	0.087	0.083	0.074	0.144	0.086	0.096	0.092	0.096	0.127	0.103	0.129	0.120	0.151	0.137	0.216	0.233	0.221	0.233	0.290
4	0.161	0.036	0.008	0.000	0.001	0.066	0.048	0.047	0.063	0.033	0.091	0.137	0.101	0.143	0.166	0.119	0.089	0.139	0.130	0.123	0.128	0.118	0.104	0.189	0.119	0.210	0.192	0.236	0.443	0.397
5	0.207	0.036	0.039	0.001	0.000	0.027	0.066	0.119	0.054	0.120	0.052	0.077	0.068	0.062	0.123	0.076	0.081	0.083	0.086	0.107	0.092	0.119	0.111	0.123	0.129	0.198	0.233	0.202	0.239	0.282
6	0.158	0.073	0.033	0.066	0.027	0.000	0.003	0.011	0.019	0.017	0.036	0.032	0.039	0.093	0.042	0.059	0.043	0.087	0.067	0.063	0.074	0.004	0.121	0.136	0.084	0.154	0.122	0.160	0.221	0.320
7	0.199	0.142	0.080	0.048	0.066	0.003	0.000	0.017	0.016	0.031	0.027	0.037	0.046	0.033	0.098	0.044	0.057	0.033	0.054	0.079	0.080	0.094	0.090	0.104	0.117	0.232	0.313	0.183	0.390	0.306
8	0.207	0.143	0.127	0.047	0.119	0.011	0.017	0.000	0.006	0.024	0.013	0.021	0.024	0.021	0.030	0.029	0.059	0.033	0.058	0.059	0.058	0.067	0.061	0.076	0.093	0.133	0.171	0.133	0.166	0.242
9	0.192	0.133	0.068	0.063	0.054	0.019	0.016	0.006	0.000	0.004	0.019	0.020	0.022	0.026	0.023	0.033	0.004	0.033	0.052	0.097	0.077	0.074	0.077	0.099	0.102	0.109	0.208	0.220	0.132	0.389
10	0.224	0.143	0.137	0.033	0.120	0.017	0.031	0.024	0.004	0.000	0.009	0.013	0.014	0.014	0.031	0.020	0.030	0.023	0.030	0.038	0.051	0.037	0.051	0.063	0.090	0.111	0.149	0.139	0.148	0.219
11	0.171	0.102	0.061	0.091	0.052	0.036	0.027	0.013	0.019	0.009	0.000	0.002	0.003	0.023	0.006	0.023	0.016	0.031	0.039	0.043	0.048	0.042	0.093	0.107	0.069	0.089	0.100	0.134	0.122	0.289
12	0.227	0.111	0.087	0.137	0.077	0.032	0.037	0.021	0.020	0.013	0.002	0.000	0.001	0.009	0.006	0.027	0.014	0.032	0.054	0.041	0.043	0.048	0.093	0.132	0.070	0.100	0.113	0.150	0.168	0.274
13	0.218	0.218	0.083	0.101	0.068	0.039	0.046	0.024	0.022	0.014	0.003	0.001	0.000	0.003	0.003	0.009	0.013	0.016	0.019	0.039	0.046	0.041	0.059	0.067	0.071	0.276	0.121	0.134	0.166	0.432
14	0.219	0.117	0.074	0.143	0.062	0.093	0.033	0.021	0.026	0.014	0.023	0.009	0.003	0.000	0.000	0.009	0.009	0.022	0.027	0.036	0.039	0.036	0.077	0.091	0.062	0.091	0.094	0.128	0.132	0.280
15	0.214	0.280	0.144	0.166	0.123	0.042	0.098	0.030	0.023	0.031	0.006	0.006	0.003	0.000	0.000	0.003	0.012	0.011	0.016	0.040	0.048	0.030	0.049	0.067	0.079	0.171	0.163	0.172	0.342	0.271
16	0.203	0.120	0.086	0.119	0.076	0.059	0.044	0.029	0.033	0.020	0.023	0.027	0.009	0.009	0.003	0.000	0.003	0.013	0.041	0.033	0.036	0.041	0.080	0.112	0.064	0.083	0.103	0.158	0.127	0.287
17	0.193	0.170	0.096	0.089	0.081	0.043	0.057	0.059	0.004	0.030	0.016	0.014	0.013	0.009	0.012	0.003	0.000	0.000	0.007	0.031	0.000	0.049	0.057	0.033	0.078	0.084	0.229	0.166	0.104	0.428
18	0.222	0.122	0.092	0.139	0.083	0.087	0.033	0.033	0.033	0.023	0.031	0.032	0.016	0.022	0.011	0.013	0.000	0.000	0.013	0.023	0.027	0.030	0.073	0.096	0.059	0.088	0.094	0.120	0.137	0.293
19	0.220	0.121	0.096	0.130	0.086	0.067	0.054	0.058	0.052	0.030	0.039	0.054	0.019	0.027	0.016	0.041	0.007	0.013	0.000	0.019	0.023	0.028	0.051	0.097	0.054	0.068	0.094	0.140	0.107	0.297
20	0.243	0.223	0.127	0.123	0.107	0.063	0.079	0.059	0.097	0.038	0.043	0.041	0.039	0.036	0.040	0.033	0.031	0.023	0.019	0.000	0.011	0.011	0.016	0.033	0.048	0.057	0.097	0.122	0.084	0.221
21	0.191	0.172	0.103	0.128	0.092	0.074	0.080	0.058	0.077	0.051	0.048	0.043	0.046	0.039	0.048	0.036	0.000	0.027	0.023	0.011	0.000	0.002	0.008	0.029	0.041	0.053	0.084	0.093	0.083	0.228
22	0.210	0.101	0.129	0.118	0.119	0.004	0.094	0.067	0.074	0.037	0.042	0.048	0.041	0.036	0.030	0.041	0.049	0.030	0.028	0.011	0.002	0.000	0.007	0.028	0.040	0.057	0.113	0.102	0.076	0.275
23	0.231	0.133	0.120	0.104	0.111	0.121	0.090	0.061	0.077	0.051	0.093	0.093	0.059	0.077	0.049	0.080	0.057	0.073	0.051	0.016	0.008	0.007	0.000	0.043	0.023	0.033	0.057	0.077	0.082	0.202
24	0.221	0.139	0.151	0.189	0.123	0.136	0.104	0.076	0.099	0.063	0.107	0.132	0.067	0.091	0.067	0.112	0.033	0.096	0.097	0.033	0.029	0.028	0.043	0.000	0.012	0.028	0.039	0.038	0.000	0.219
25	0.203	0.183	0.137	0.119	0.129	0.084	0.117	0.093	0.102	0.090	0.069	0.070	0.071	0.062	0.079	0.064	0.078	0.059	0.054	0.048	0.041	0.040	0.023	0.012	0.000	0.009	0.029	0.031	0.026	0.137
26	0.275	0.474	0.216	0.210	0.198	0.154	0.232	0.133	0.109	0.111	0.089	0.100	0.276	0.091	0.171	0.083	0.084	0.088	0.068	0.057	0.053	0.057	0.033	0.028	0.009	0.000	0.010	0.023	0.038	0.187
27	0.323	0.483	0.233	0.192	0.233	0.122	0.313	0.171	0.208	0.149	0.100	0.113	0.121	0.094	0.163	0.103	0.229	0.094	0.094	0.097	0.084	0.113	0.057	0.039	0.029	0.010	0.000	0.017	0.016	0.174
28	0.290	0.423	0.221	0.236	0.202	0.160	0.183	0.133	0.220	0.139	0.134	0.150	0.134	0.128	0.172	0.158	0.166	0.120	0.140	0.122	0.093	0.102	0.077	0.038	0.031	0.023	0.017	0.000	0.003	0.213
29	0.310	0.333	0.233	0.443	0.239	0.221	0.390	0.166	0.132	0.148	0.122	0.168	0.166	0.132	0.342	0.127	0.104	0.137	0.107	0.084	0.083	0.076	0.082	0.000	0.026	0.038	0.016	0.003	0.000	0.139
30	0.391	0.424	0.290	0.397	0.282	0.320	0.306	0.242	0.389	0.219	0.289	0.274	0.432	0.280	0.271	0.287	0.428	0.293	0.297	0.221	0.228	0.275	0.202	0.219	0.137	0.187	0.174	0.213	0.139	0.000

Table 13: Similarity Matrix for 30 JIEDDO Proposals

30	29	28	27	26	25	24	23	22	21	20	19	18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	
1.000	0.878	0.824	0.852	0.842	0.880	0.820	0.792	0.784	0.815	0.819	0.771	0.772	0.701	0.777	0.787	0.781	0.689	0.785	0.770	0.820	0.629	0.805	0.664	0.754	0.780	0.716	0.771	0.702	0.719	30
0.878	1.000	0.997	0.985	0.965	0.974	0.945	0.924	0.929	0.922	0.925	0.905	0.880	0.900	0.888	0.745	0.864	0.858	0.850	0.891	0.871	0.865	0.857	0.719	0.819	0.807	0.695	0.797	0.644	0.705	29
0.824	0.997	1.000	0.985	0.977	0.970	0.945	0.929	0.908	0.915	0.892	0.877	0.888	0.858	0.864	0.855	0.887	0.882	0.869	0.882	0.878	0.820	0.868	0.845	0.862	0.832	0.790	0.819	0.705	0.772	28
0.852	0.985	0.985	1.000	0.990	0.972	0.965	0.940	0.897	0.922	0.912	0.914	0.914	0.814	0.905	0.866	0.914	0.892	0.897	0.909	0.870	0.828	0.854	0.762	0.891	0.810	0.839	0.797	0.674	0.756	27
0.842	0.965	0.977	0.990	1.000	0.991	0.975	0.948	0.940	0.949	0.940	0.930	0.919	0.925	0.922	0.854	0.917	0.784	0.909	0.918	0.900	0.902	0.865	0.812	0.807	0.855	0.820	0.822	0.678	0.784	26
0.880	0.974	0.970	0.972	0.991	1.000	0.988	0.970	0.962	0.960	0.955	0.948	0.945	0.928	0.959	0.927	0.942	0.954	0.955	0.955	0.918	0.908	0.915	0.890	0.925	0.880	0.895	0.880	0.840	0.850	25
0.820	0.945	0.945	0.965	0.975	0.988	1.000	0.958	0.972	0.972	0.968	0.911	0.912	0.948	0.899	0.957	0.917	0.957	0.883	0.905	0.941	0.910	0.929	0.900	0.880	0.891	0.841	0.864	0.865	0.819	24
0.792	0.924	0.929	0.940	0.948	0.970	0.958	1.000	0.995	0.992	0.984	0.951	0.952	0.965	0.920	0.954	0.928	0.944	0.915	0.915	0.951	0.928	0.942	0.917	0.892	0.900	0.859	0.895	0.800	0.815	23
0.784	0.929	0.908	0.897	0.940	0.962	0.972	0.995	1.000	0.998	0.989	0.972	0.971	0.955	0.961	0.952	0.965	0.900	0.955	0.959	0.940	0.951	0.937	0.914	0.940	0.894	0.894	0.880	0.861	0.825	22
0.815	0.922	0.915	0.922	0.949	0.960	0.972	0.992	0.998	1.000	0.989	0.977	0.974	0.945	0.966	0.954	0.963	0.956	0.959	0.954	0.952	0.928	0.945	0.921	0.931	0.915	0.887	0.905	0.855	0.839	21
0.819	0.925	0.892	0.912	0.940	0.955	0.968	0.984	0.989	0.989	1.000	0.981	0.978	0.951	0.968	0.962	0.965	0.962	0.961	0.957	0.945	0.912	0.944	0.927	0.939	0.904	0.890	0.887	0.816	0.805	20
0.771	0.905	0.877	0.914	0.930	0.948	0.911	0.951	0.972	0.977	0.981	1.000	0.980	0.995	0.961	0.984	0.975	0.981	0.948	0.962	0.971	0.951	0.965	0.949	0.957	0.921	0.885	0.912	0.892	0.820	19
0.772	0.880	0.888	0.914	0.919	0.945	0.912	0.952	0.971	0.974	0.978	0.980	1.000	1.000	0.987	0.990	0.979	0.984	0.950	0.970	0.970	0.960	0.968	0.949	0.920	0.925	0.878	0.910	0.892	0.818	18
0.701	0.900	0.858	0.814	0.925	0.928	0.948	0.965	0.955	0.945	0.951	0.995	1.000	1.000	0.995	0.988	0.991	0.985	0.987	0.985	0.971	0.940	0.962	0.940	0.959	0.925	0.918	0.912	0.850	0.857	17
0.777	0.888	0.864	0.905	0.922	0.959	0.899	0.920	0.961	0.966	0.968	0.961	0.987	0.995	1.000	0.995	0.991	0.991	0.974	0.978	0.980	0.960	0.972	0.958	0.944	0.929	0.894	0.921	0.895	0.850	16
0.787	0.745	0.855	0.866	0.854	0.927	0.957	0.954	0.952	0.954	0.962	0.984	0.990	0.988	0.995	1.000	1.000	0.995	0.994	0.994	0.970	0.975	0.955	0.911	0.900	0.869	0.904	0.874	0.782	0.824	15
0.781	0.864	0.887	0.914	0.917	0.942	0.917	0.928	0.965	0.963	0.965	0.975	0.979	0.991	0.991	1.000	1.000	0.995	0.991	0.977	0.980	0.975	0.979	0.900	0.915	0.942	0.875	0.951	0.895	0.820	14
0.689	0.858	0.882	0.892	0.784	0.954	0.957	0.944	0.900	0.956	0.962	0.981	0.984	0.985	0.991	0.995	0.995	1.000	0.999	0.997	0.980	0.979	0.977	0.930	0.944	0.937	0.908	0.924	0.821	0.821	13
0.785	0.850	0.869	0.897	0.909	0.955	0.883	0.915	0.955	0.959	0.961	0.948	0.950	0.987	0.974	0.994	0.991	0.999	1.000	0.998	0.988	0.981	0.979	0.965	0.951	0.929	0.879	0.920	0.900	0.815	12
0.770	0.891	0.882	0.909	0.918	0.955	0.905	0.915	0.959	0.954	0.957	0.962	0.970	0.985	0.978	0.994	0.977	0.997	0.998	1.000	0.991	0.981	0.985	0.974	0.947	0.951	0.917	0.942	0.908	0.854	11
0.820	0.871	0.878	0.870	0.900	0.918	0.941	0.951	0.940	0.952	0.945	0.971	0.970	0.971	0.980	0.970	0.980	0.980	0.988	0.991	1.000	0.990	0.977	0.970	0.965	0.888	0.948	0.864	0.875	0.817	10
0.629	0.865	0.820	0.828	0.902	0.908	0.910	0.928	0.951	0.928	0.912	0.951	0.960	0.940	0.960	0.975	0.975	0.979	0.981	0.981	0.990	1.000	0.994	0.984	0.981	0.949	0.941	0.930	0.862	0.839	9
0.805	0.857	0.868	0.854	0.865	0.915	0.929	0.942	0.937	0.945	0.944	0.965	0.968	0.962	0.972	0.955	0.979	0.977	0.979	0.985	0.977	0.994	1.000	0.985	0.989	0.894	0.955	0.868	0.874	0.829	8
0.664	0.719	0.845	0.762	0.812	0.890	0.900	0.917	0.914	0.921	0.927	0.949	0.949	0.940	0.958	0.911	0.900	0.930	0.965	0.974	0.970	0.984	0.985	1.000	0.995	0.958	0.954	0.920	0.870	0.854	7
0.754	0.819	0.862	0.891	0.807	0.925	0.880	0.892	0.940	0.931	0.939	0.957	0.920	0.959	0.944	0.900	0.915	0.944	0.951	0.947	0.965	0.981	0.989	0.995	1.000	0.974	0.944	0.900	0.930	0.879	6
0.780	0.807	0.832	0.810	0.855	0.880	0.891	0.900	0.894	0.915	0.904	0.921	0.925	0.925	0.929	0.869	0.942	0.937	0.929	0.951	0.888	0.949	0.894	0.958	0.974	1.000	1.000	0.965	0.932	0.829	5
0.716	0.695	0.790	0.839	0.820	0.895	0.841	0.859	0.894	0.887	0.890	0.885	0.878	0.918	0.894	0.904	0.875	0.908	0.879	0.917	0.948	0.941	0.955	0.954	0.944	1.000	1.000	0.992	0.932	0.861	4
0.771	0.797	0.819	0.797	0.822	0.880	0.864	0.895	0.880	0.905	0.887	0.912	0.910	0.912	0.921	0.874	0.951	0.924	0.920	0.942	0.864	0.930	0.868	0.920	0.900	0.965	0.992	1.000	0.955	0.829	3
0.702	0.644	0.705	0.674	0.678	0.840	0.865	0.800	0.861	0.855	0.816	0.892	0.892	0.850	0.895	0.782	0.895	0.821	0.900	0.908	0.875	0.862	0.874	0.870	0.930	0.932	0.932	0.955	1.000	0.915	2
0.719	0.705	0.772	0.756	0.784	0.850	0.819	0.815	0.825	0.839	0.805	0.820	0.818	0.857	0.850	0.824	0.820	0.821	0.815	0.854	0.817	0.839	0.829	0.854	0.879	0.829	0.861	0.829	0.915	1.000	1

Appendix C: Proposal Rank Comparison Images

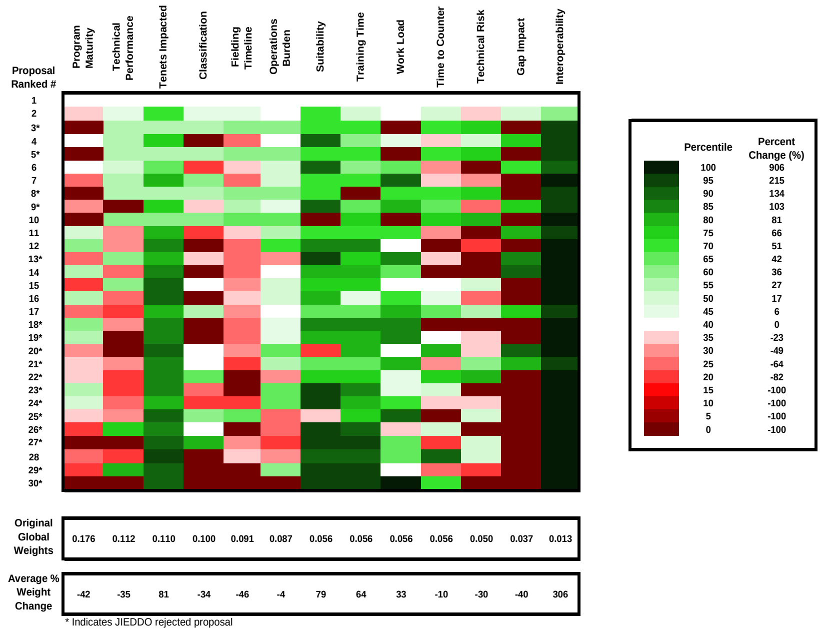


Figure 34: Proposal #1 Percent Change

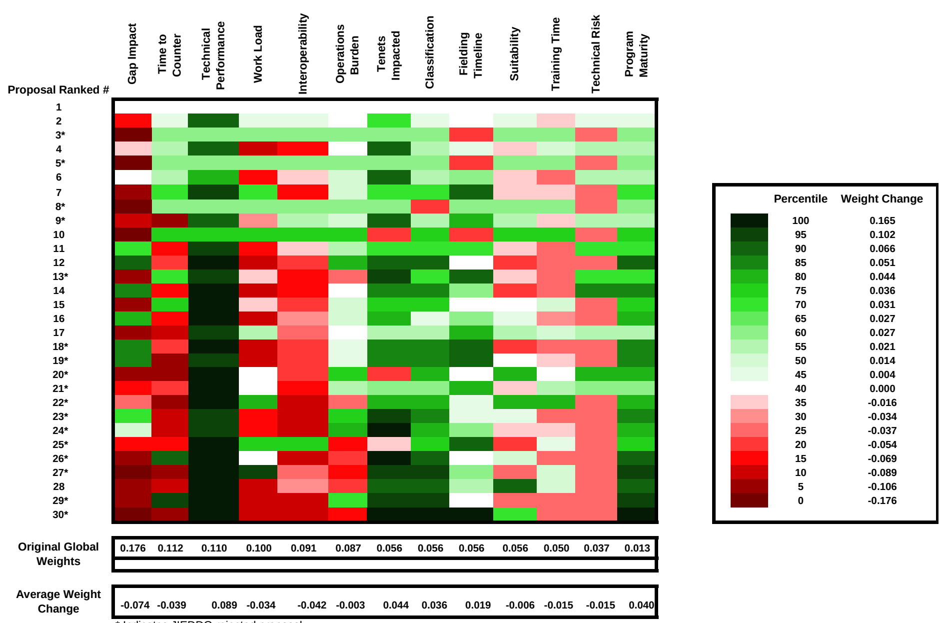


Figure 35: Proposal #2 Percent Change

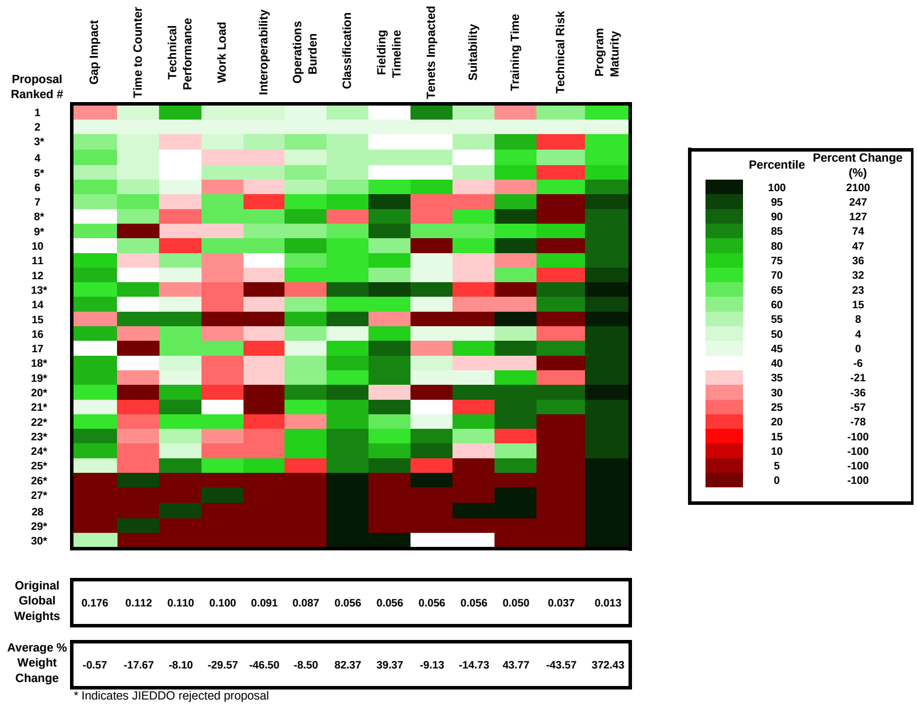


Figure 36: Proposal #2 Percent Change

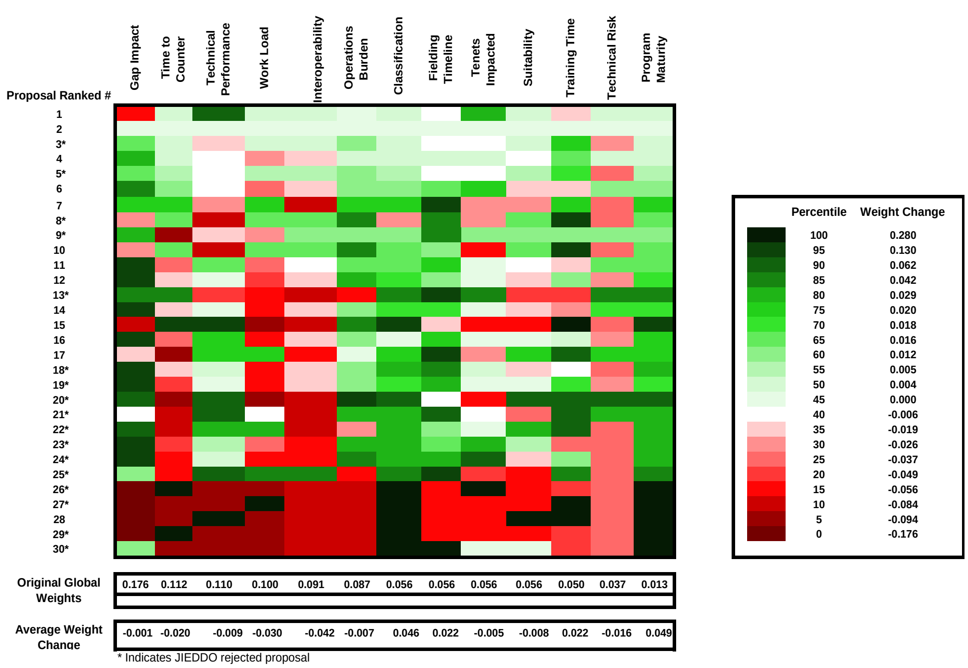


Figure 37: Proposal #3 Weight Change

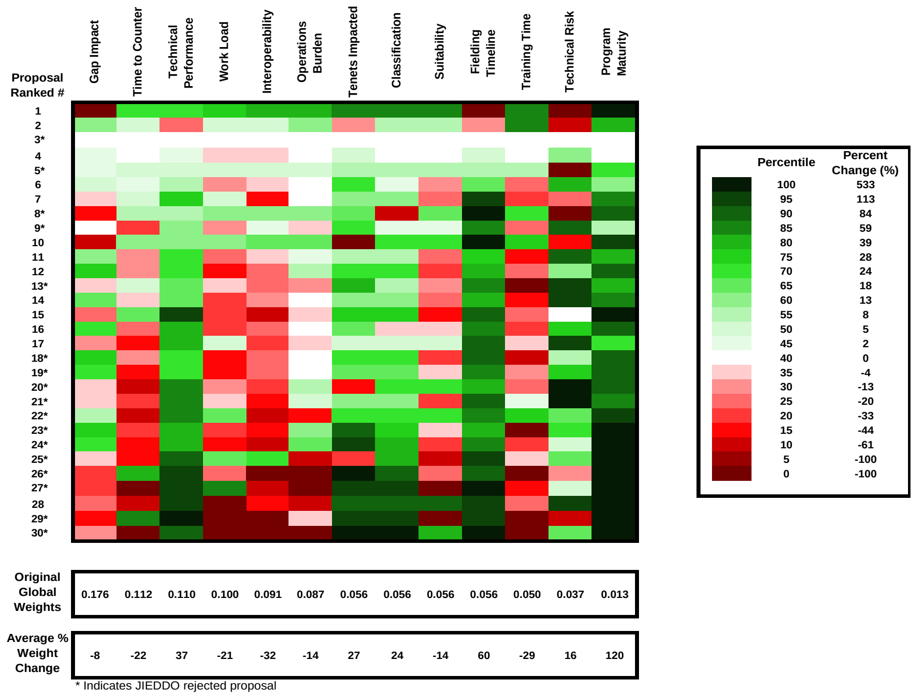


Figure 38: Proposal #3 Percent Change

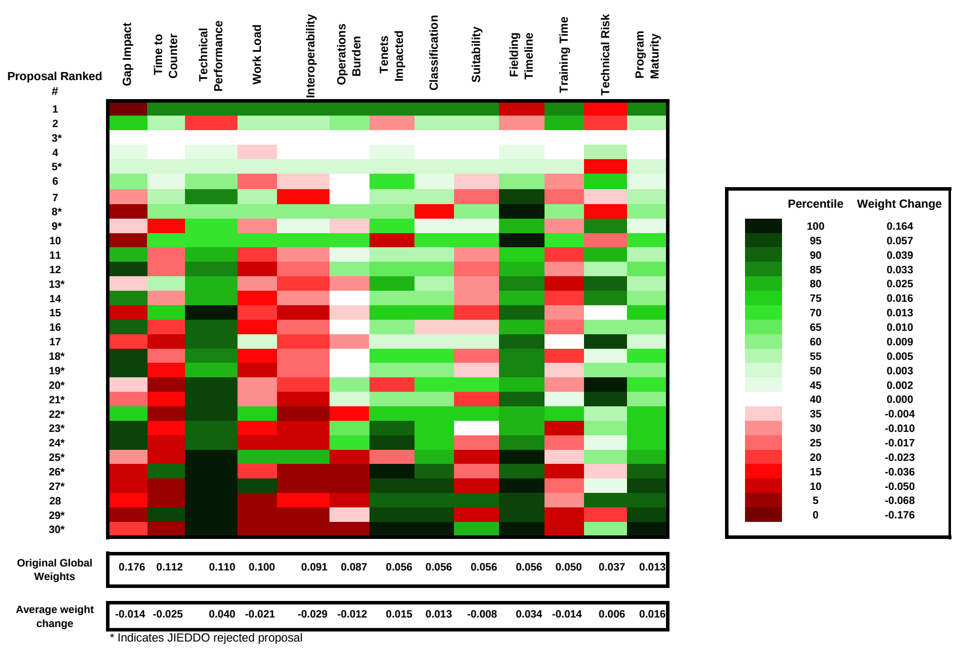


Figure 39: Proposal #3 Weight Change

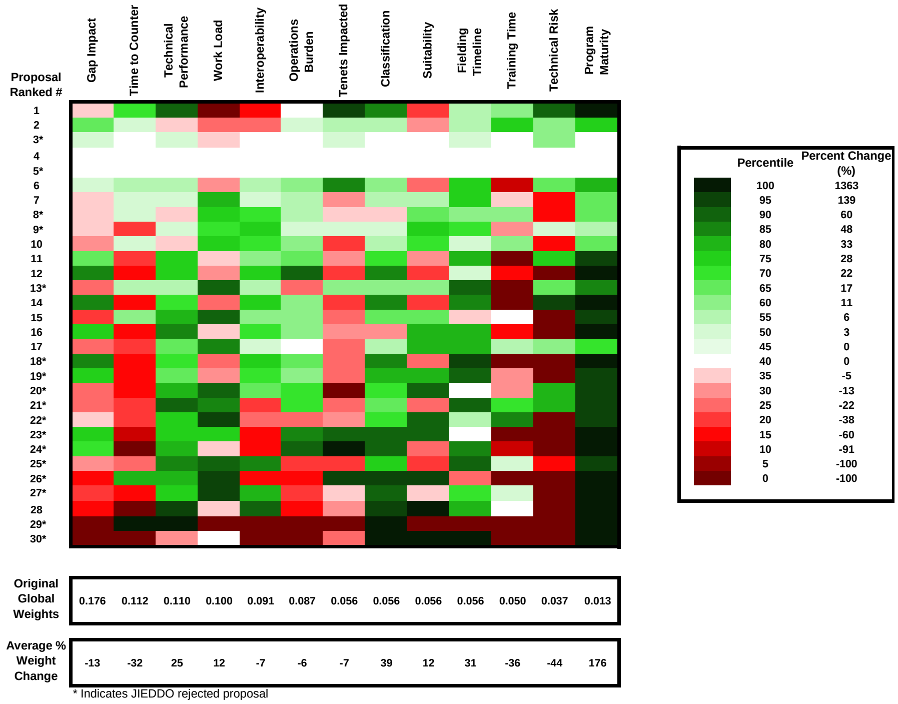


Figure 40: Proposal #4 Percent Change

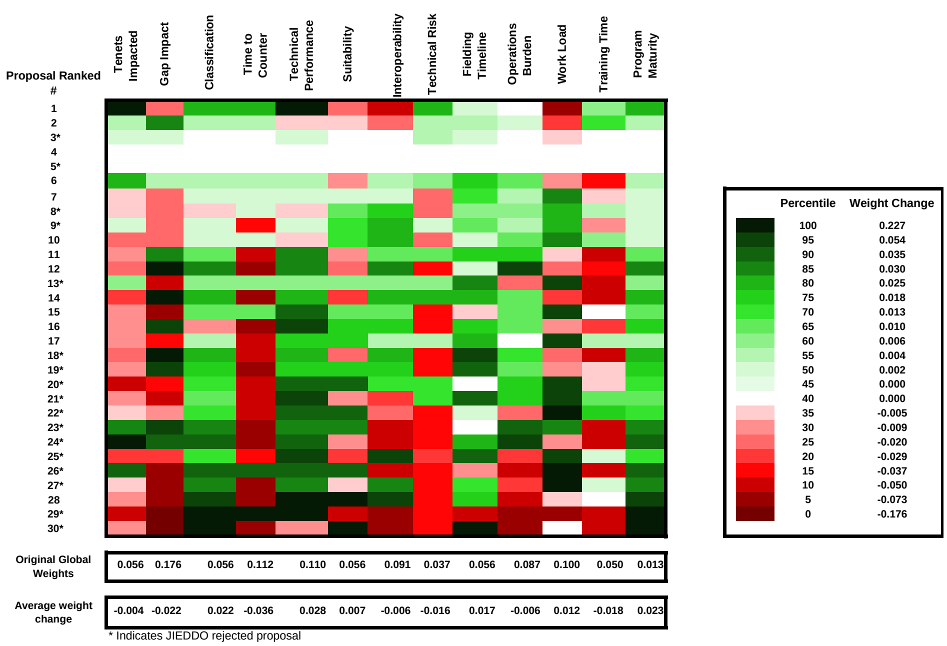


Figure 41: Proposal #4 Weight Change

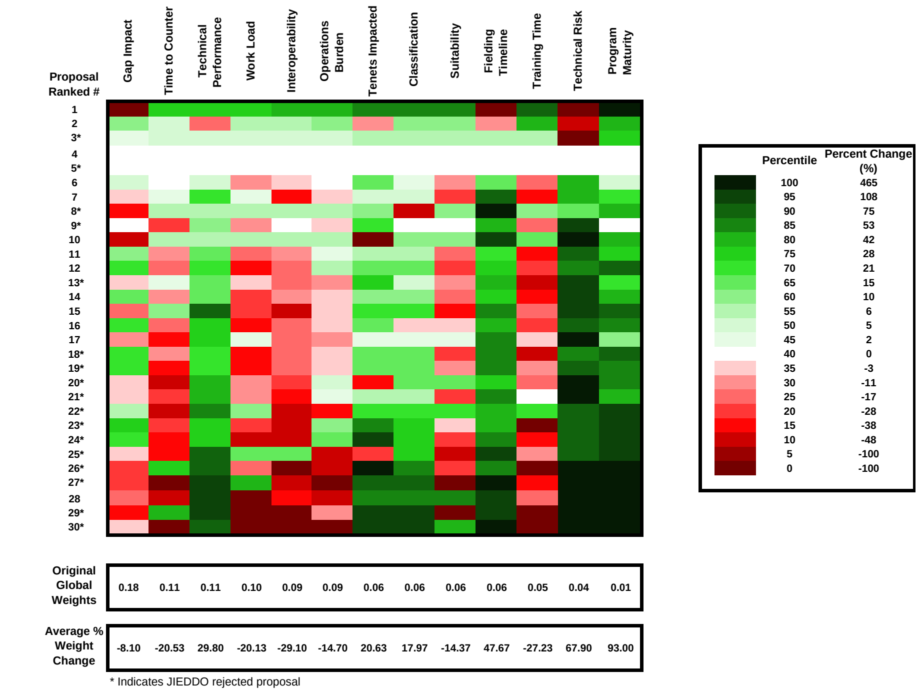


Figure 42: Proposal #5 Percent Change

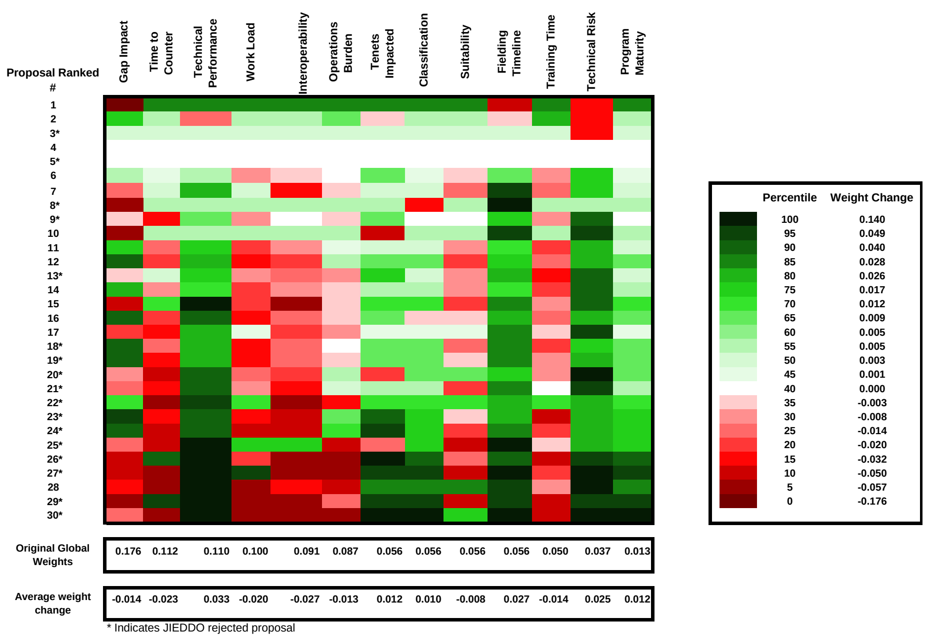
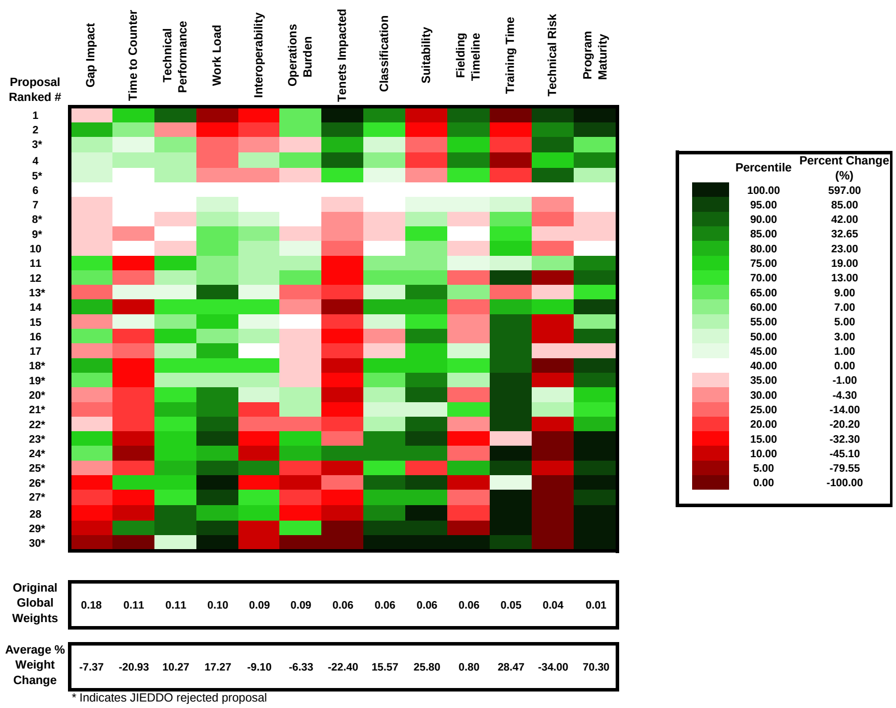


Figure 43: Proposal #5 Weight Change



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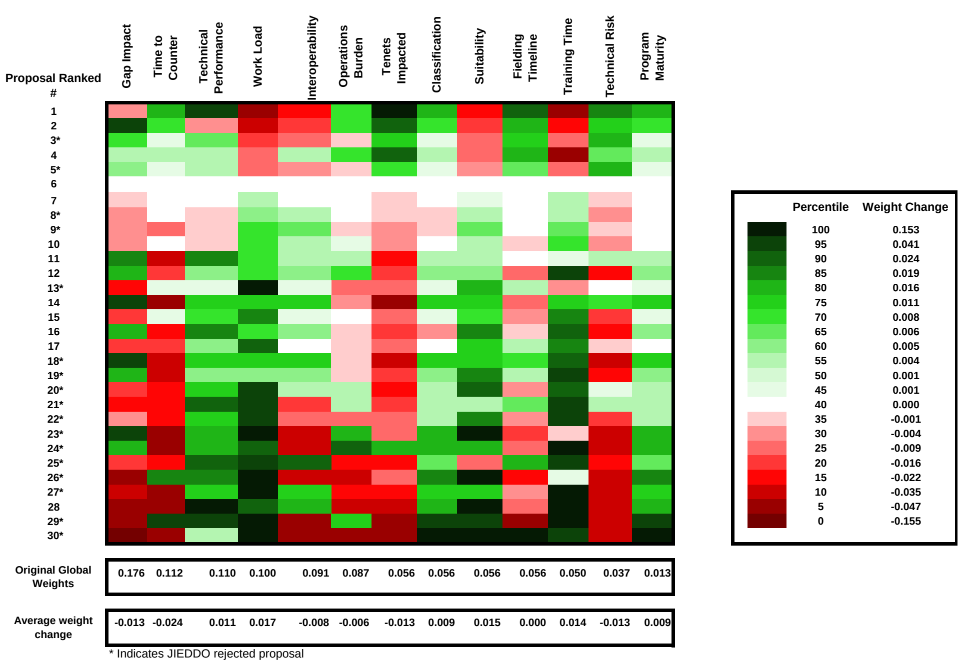

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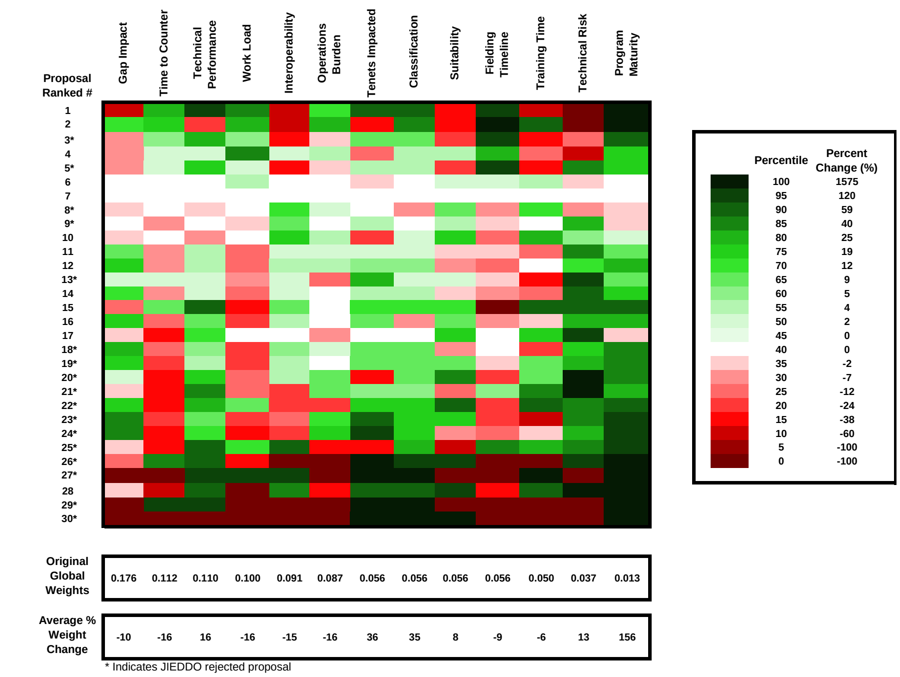

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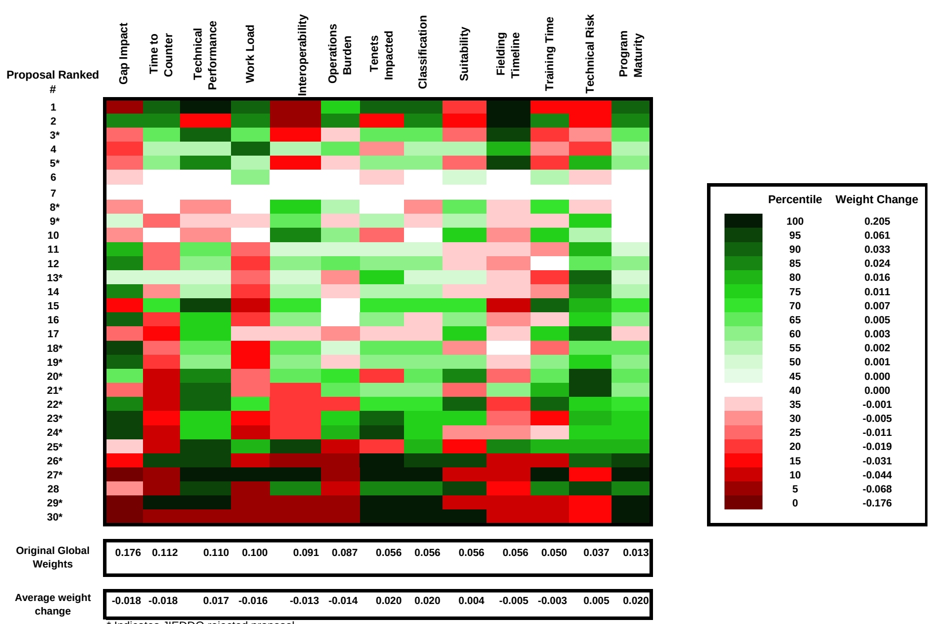

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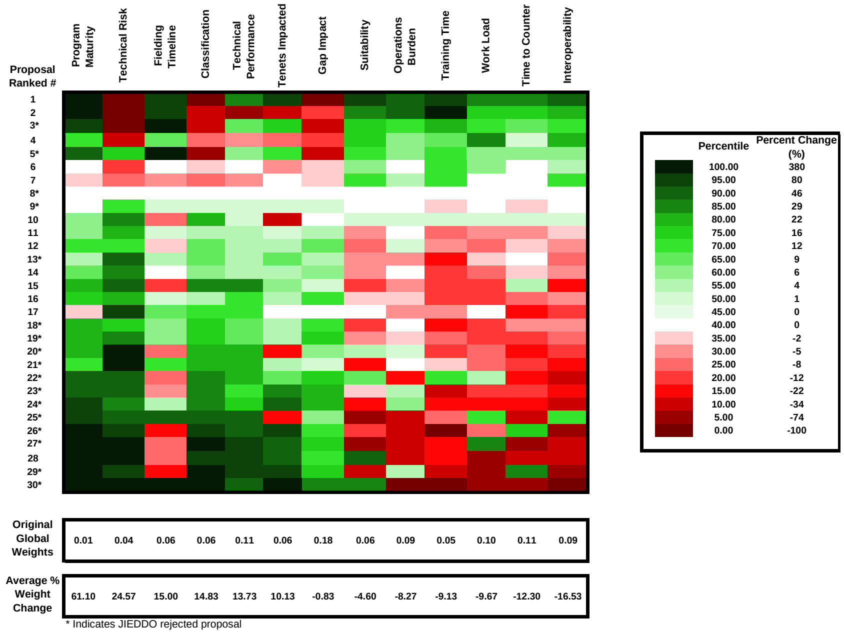

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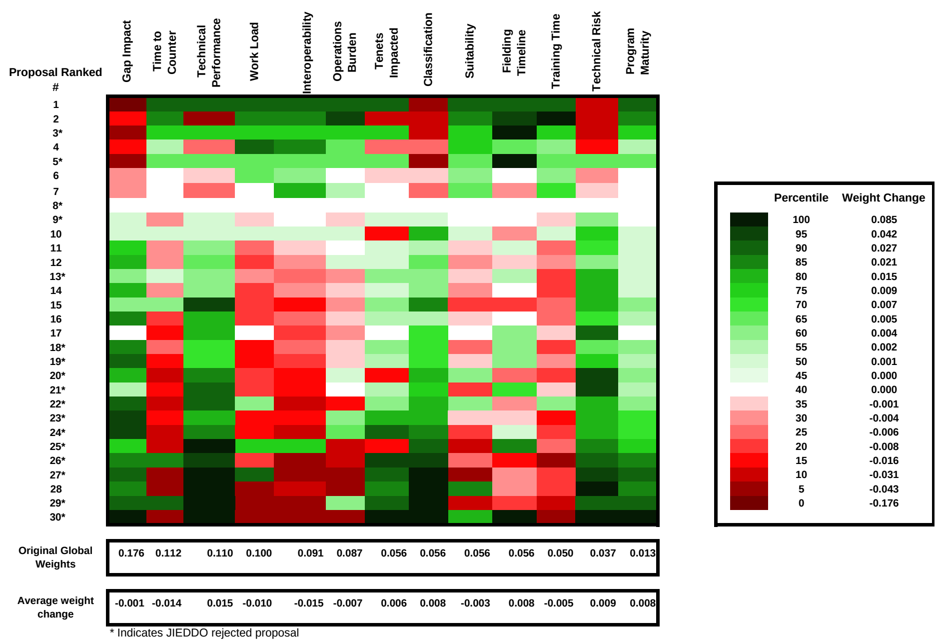

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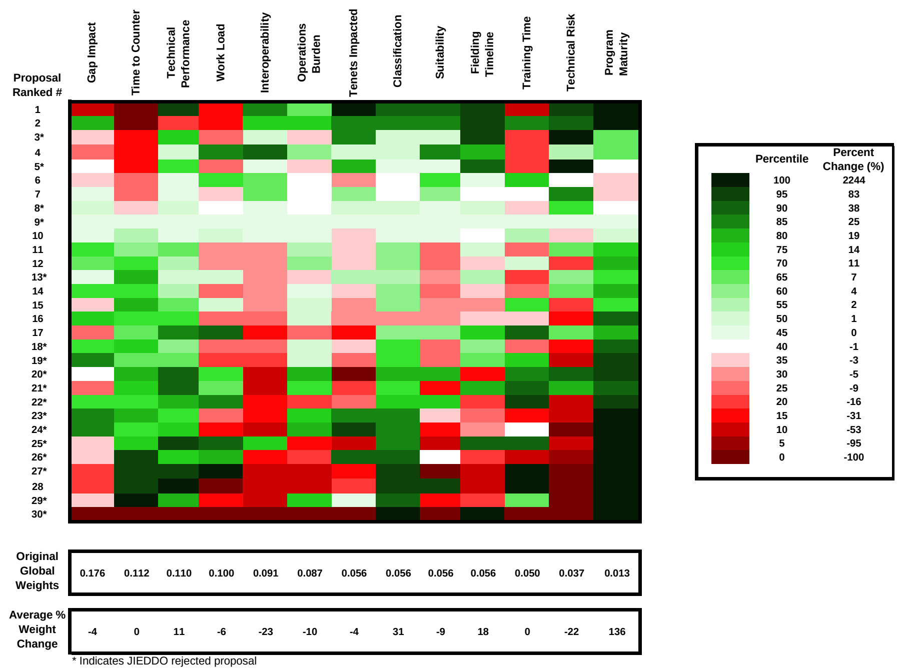

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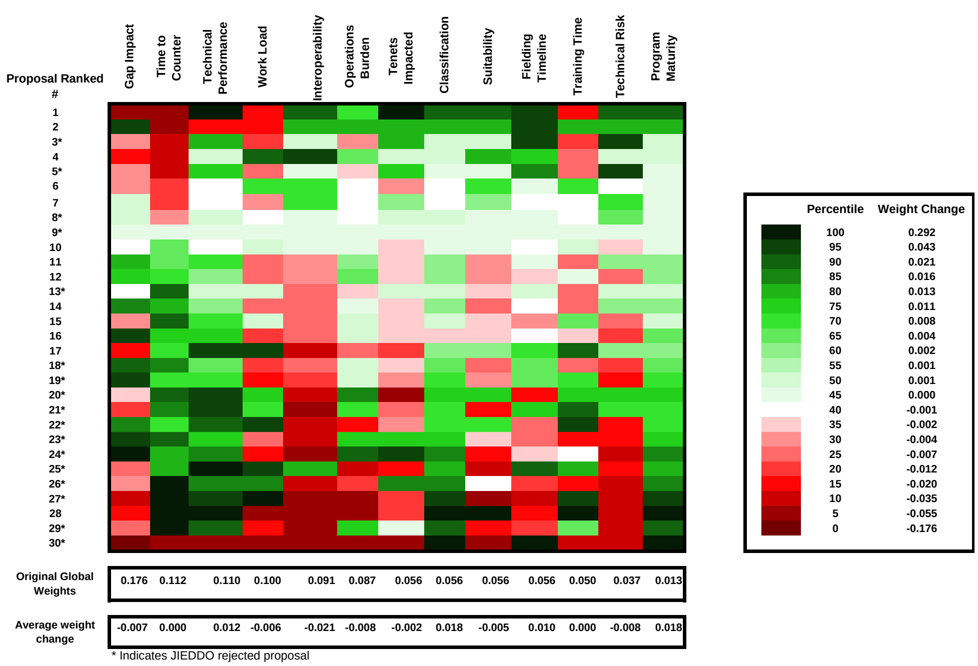

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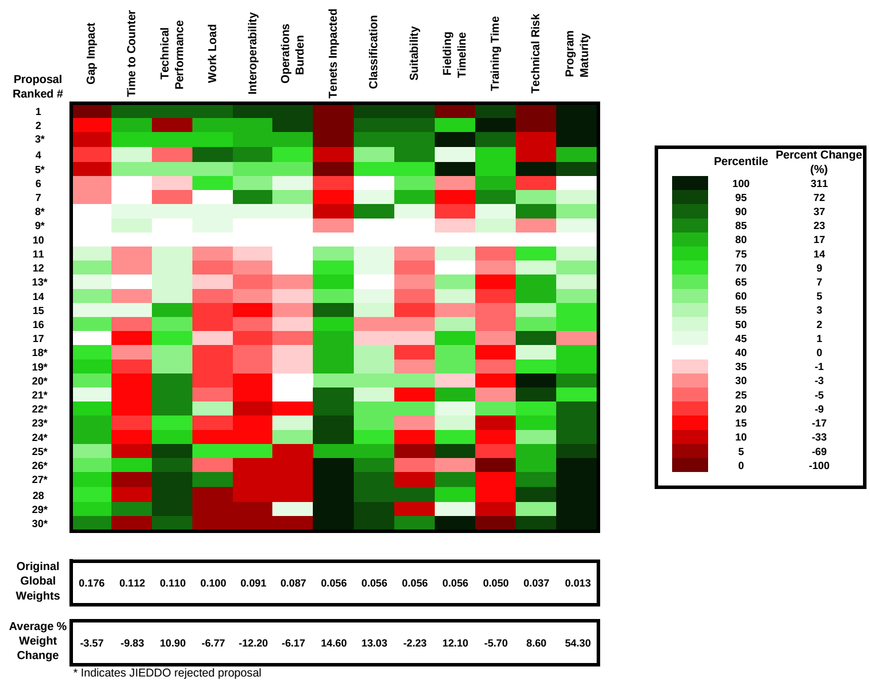

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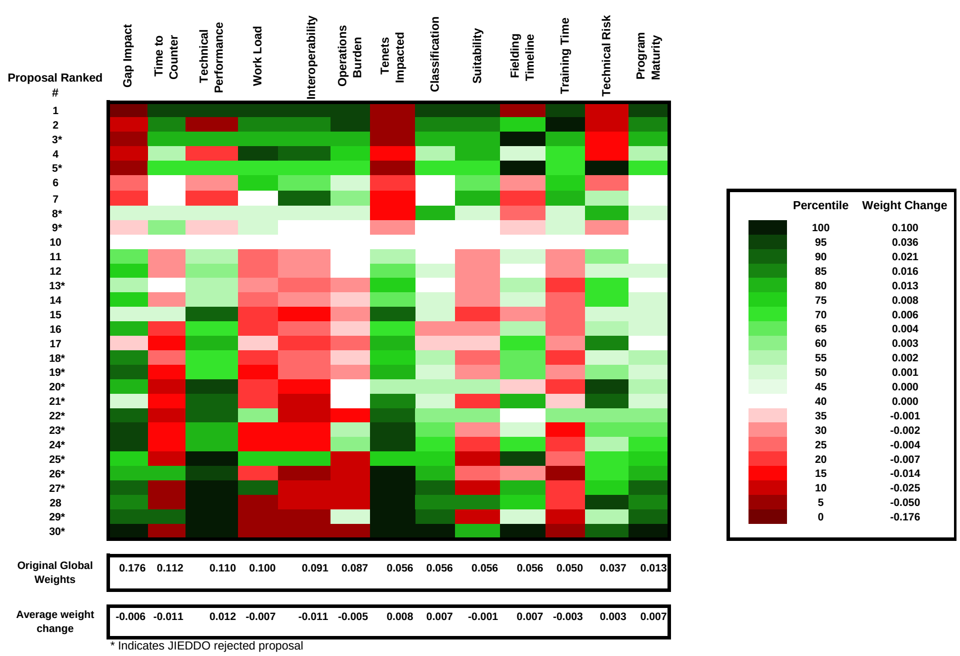


Figure 53: Proposal #10 Weight Change

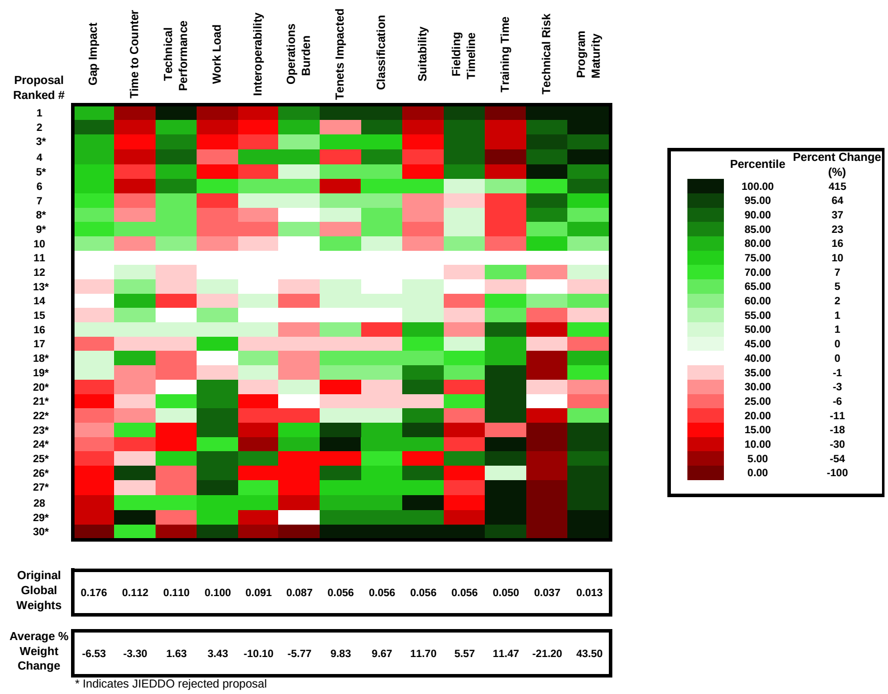


Figure 54: Proposal #11 Percent Change

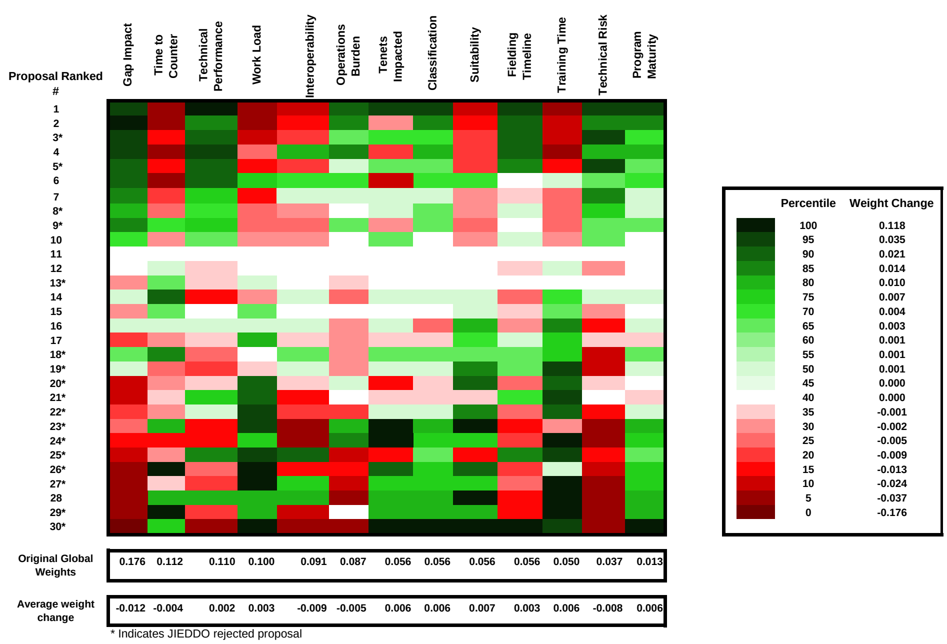
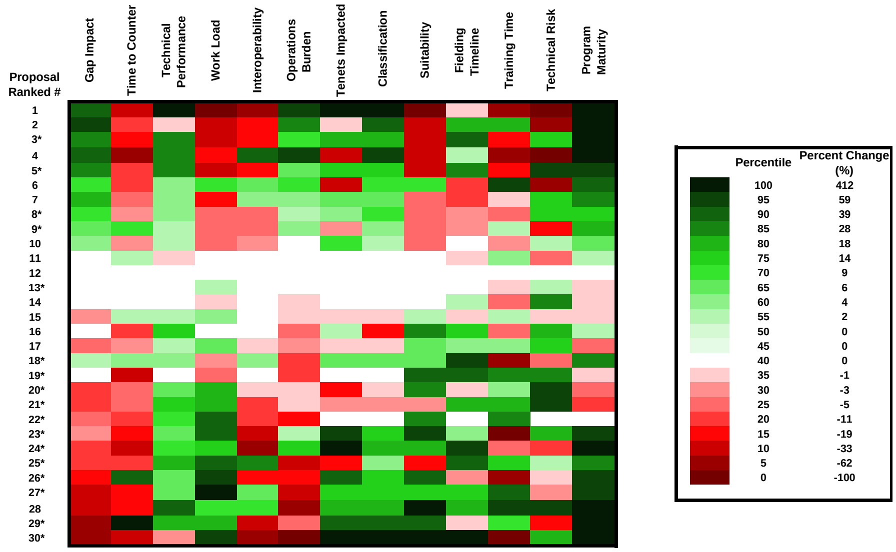


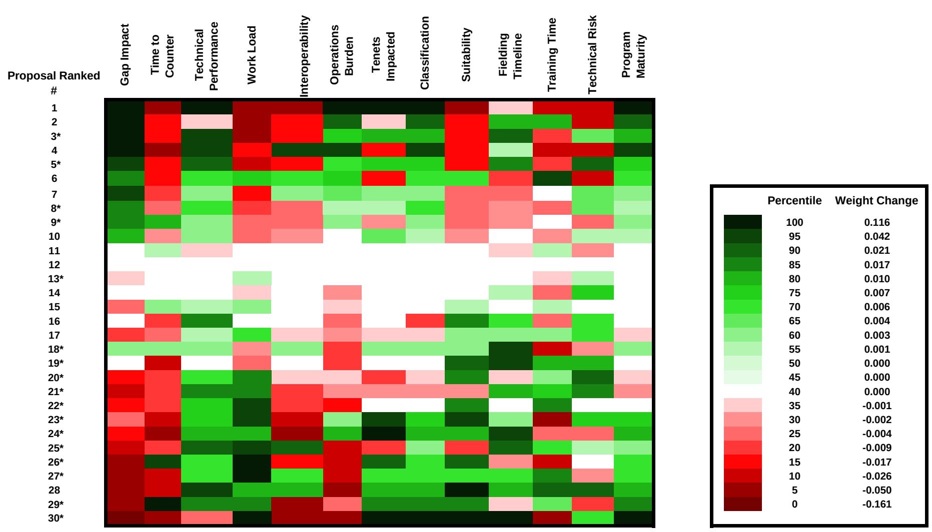
Figure 55: Proposal #11 Weight Change



Original Global Weights	0.176	0.112	0.110	0.100	0.091	0.087	0.056	0.056	0.056	0.056	0.050	0.037	0.013
Average % Weight Change	-5.83	-12.17	10.30	0.87	-12.83	-6.13	13.40	13.13	9.03	15.50	-12.37	-4.03	58.67

* Indicates JIEDDO rejected proposal

Figure 56: Proposal #12 Percent Change



Original Global Weights	0.176	0.112	0.110	0.100	0.091	0.087	0.056	0.056	0.056	0.056	0.050	0.037	0.013
Average weight change	-0.010	-0.014	0.011	0.001	-0.012	-0.005	0.007	0.007	0.005	0.009	-0.006	-0.001	0.008

* Indicates JIEDDO rejected proposal

Figure 53: Proposal #12 Weight Change

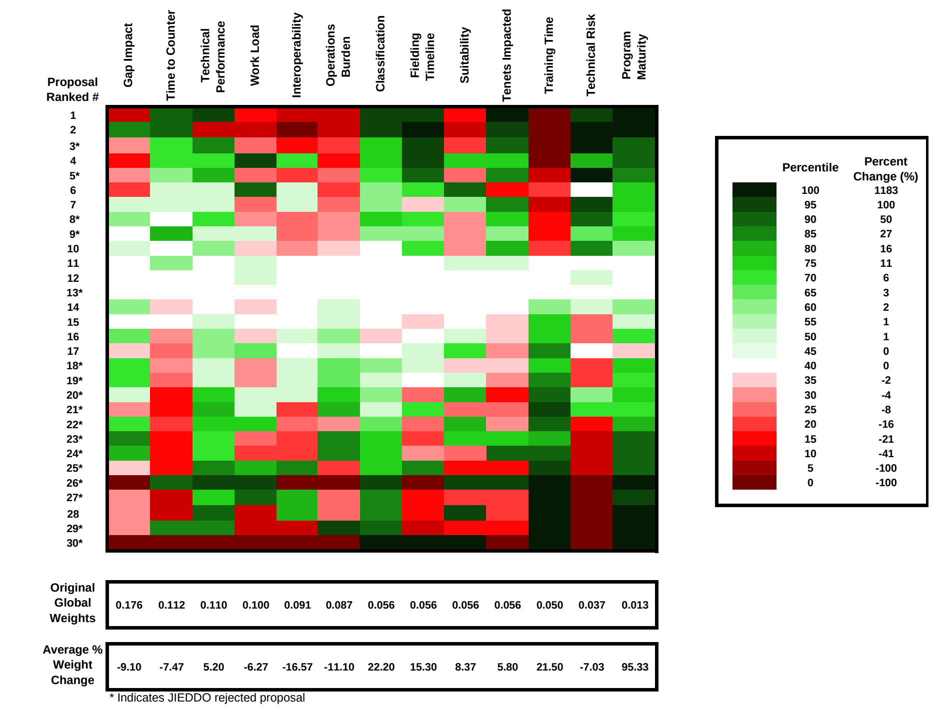


Figure 58: Proposal #13 Percent Change

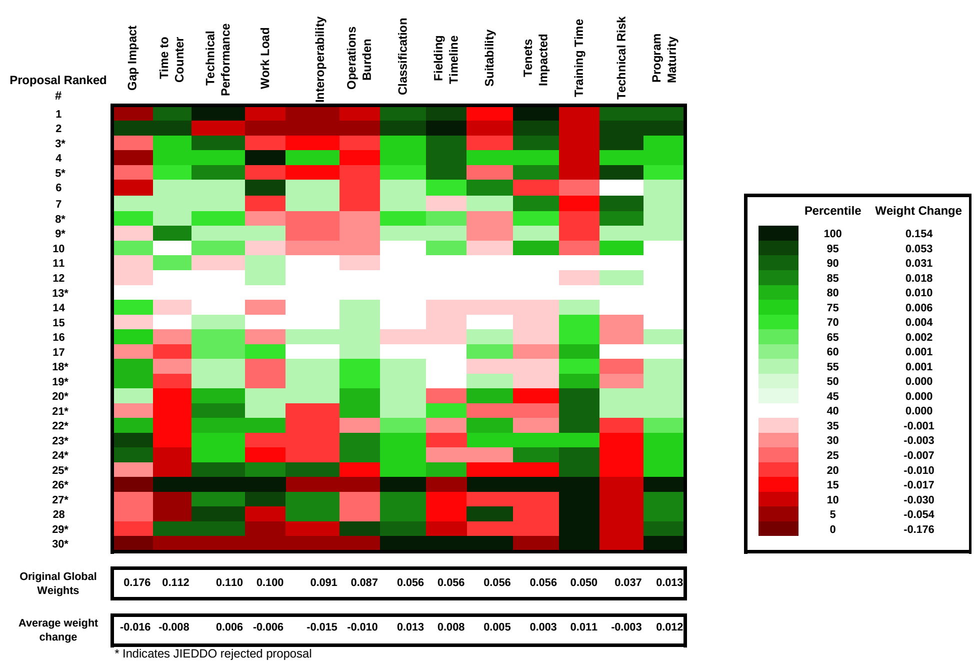


Figure 59: Proposal #13 Weight Change

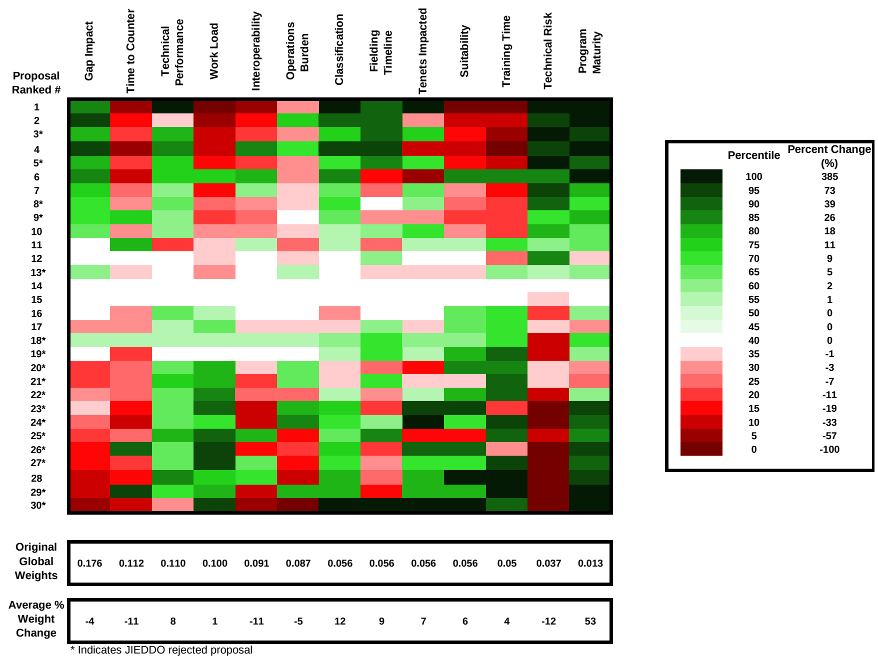


Figure 60: Proposal #14 Percent Change

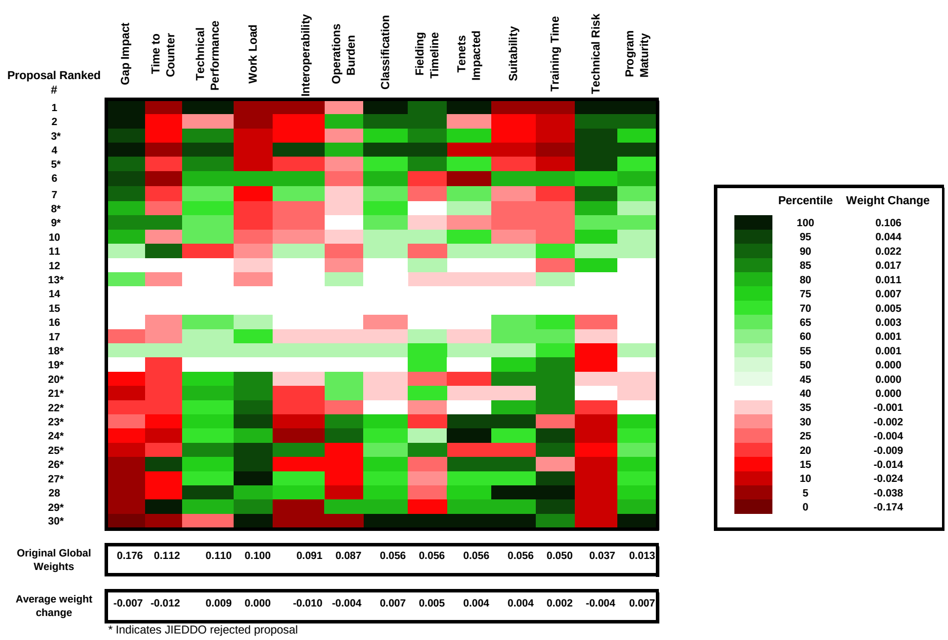
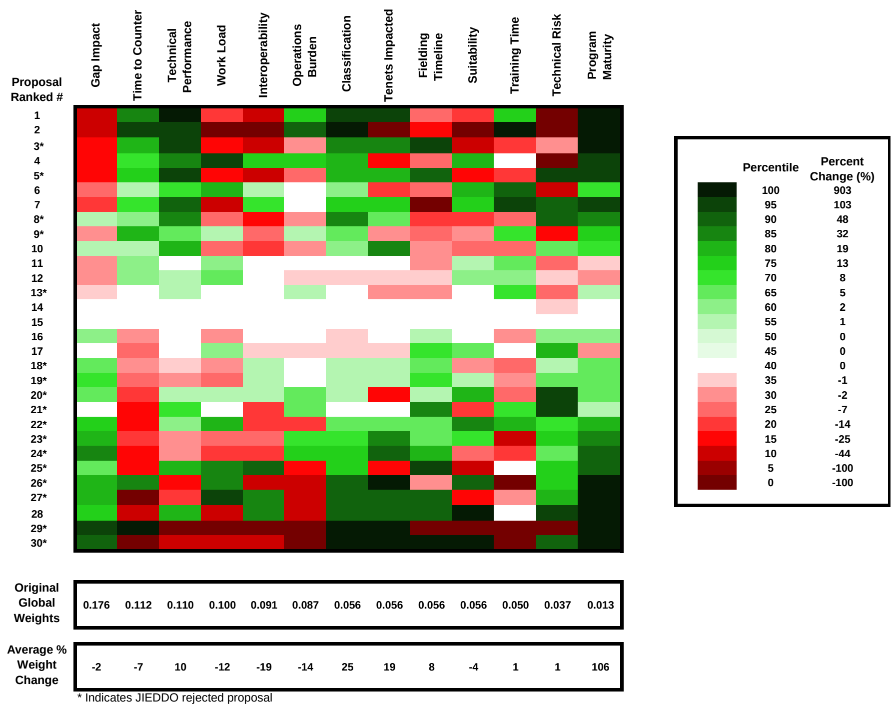


Figure 61: Proposal #14 Weight Change



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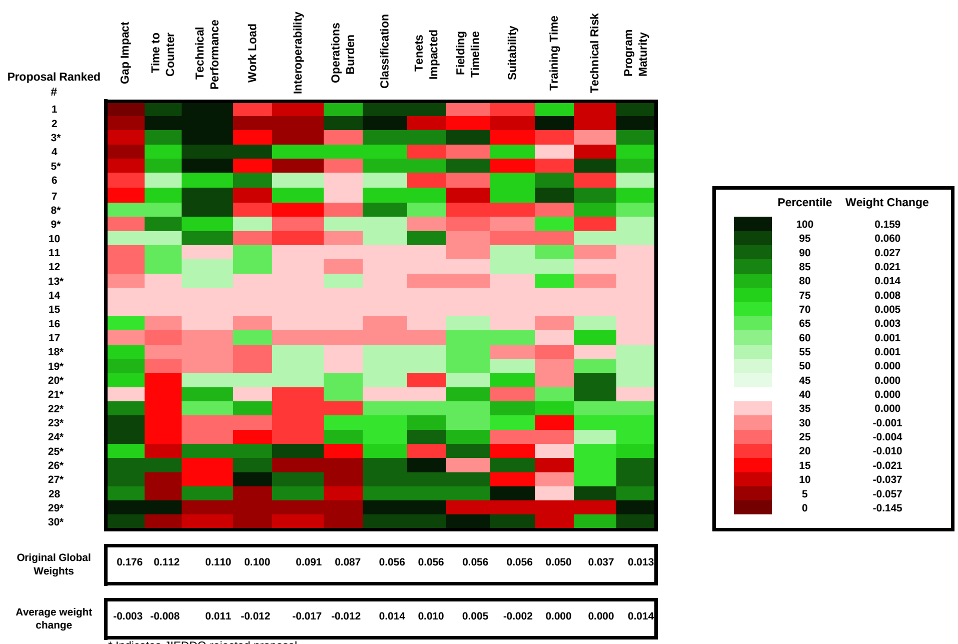

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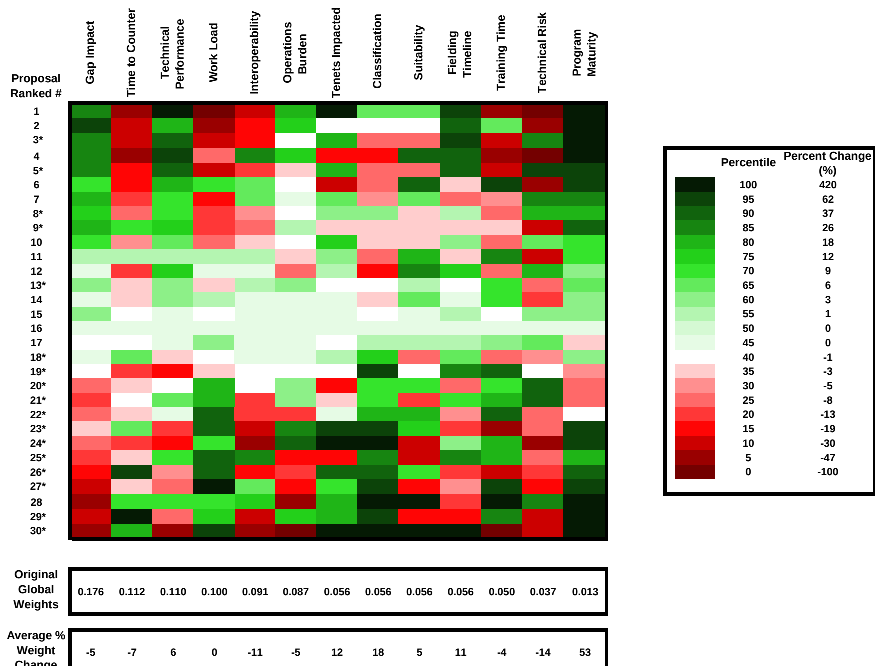

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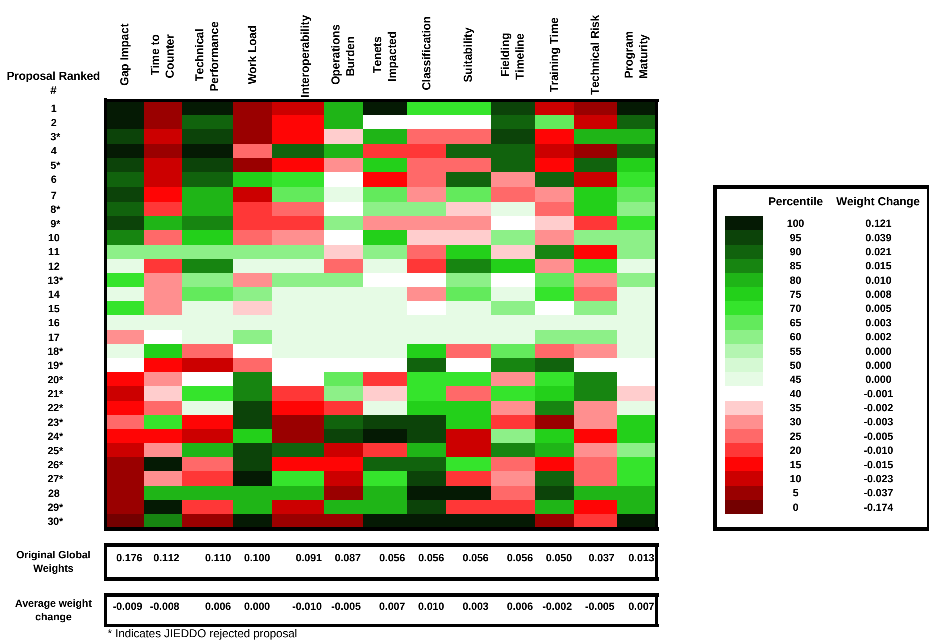

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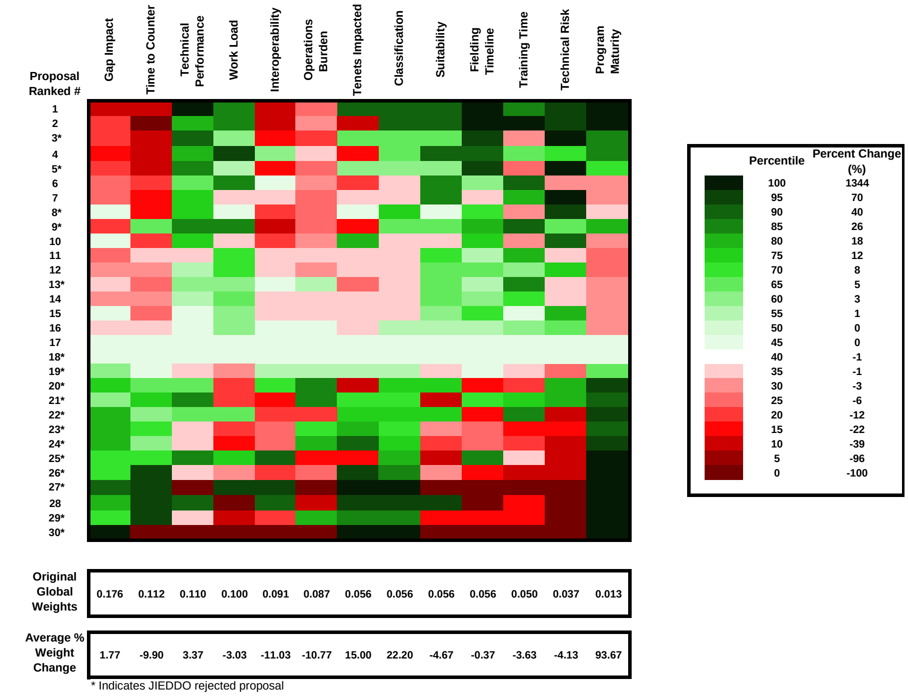

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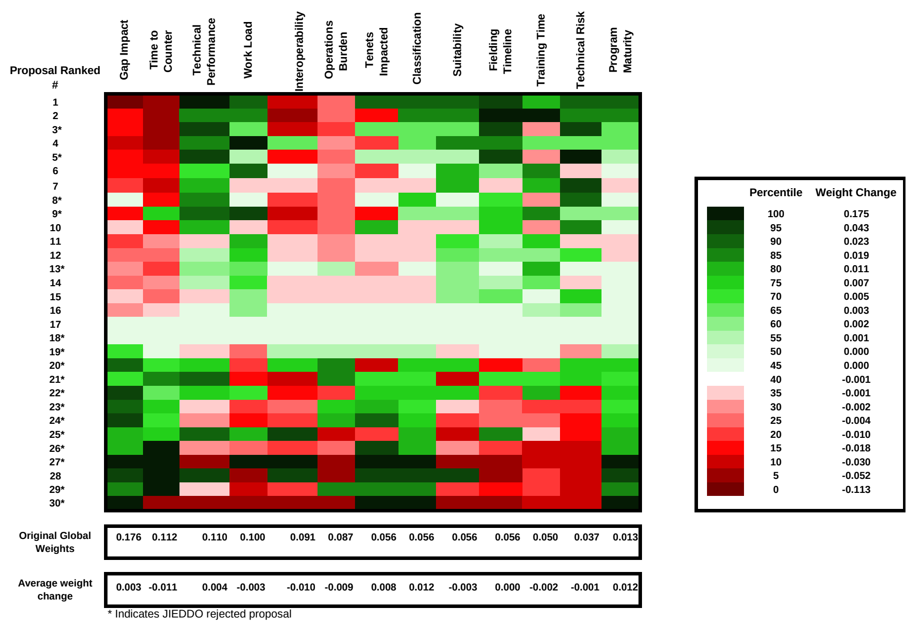

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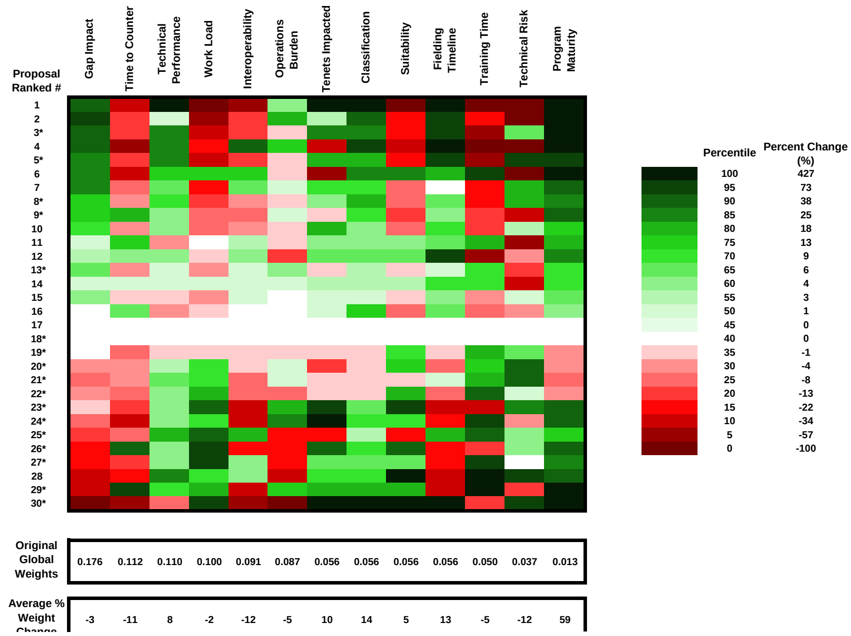

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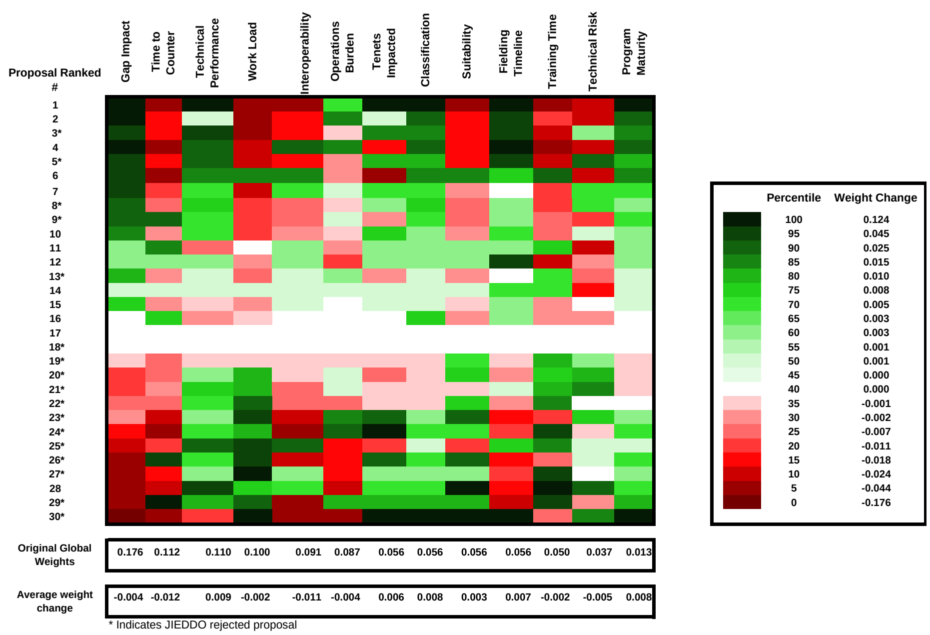

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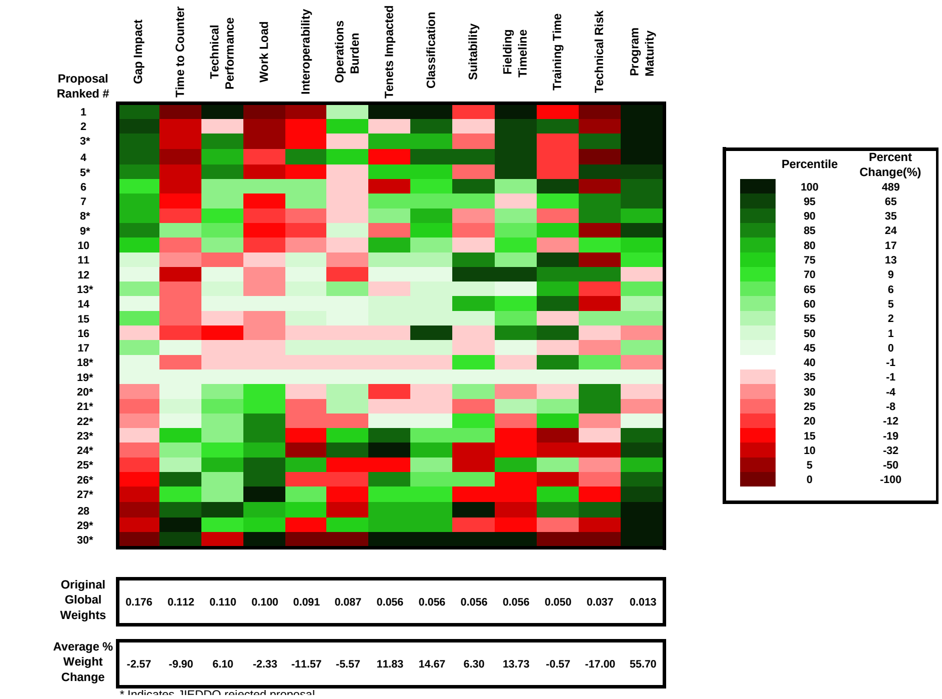

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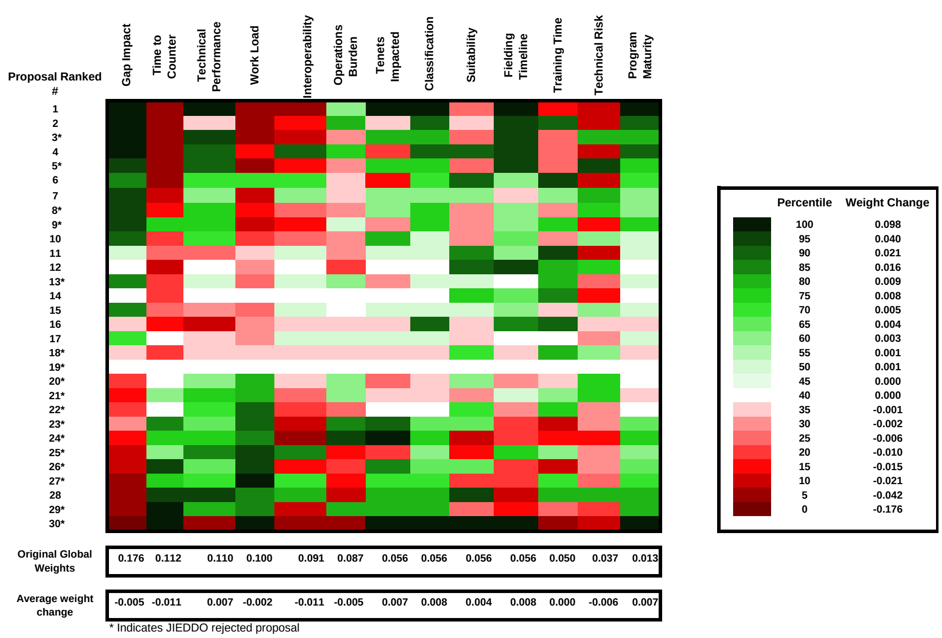

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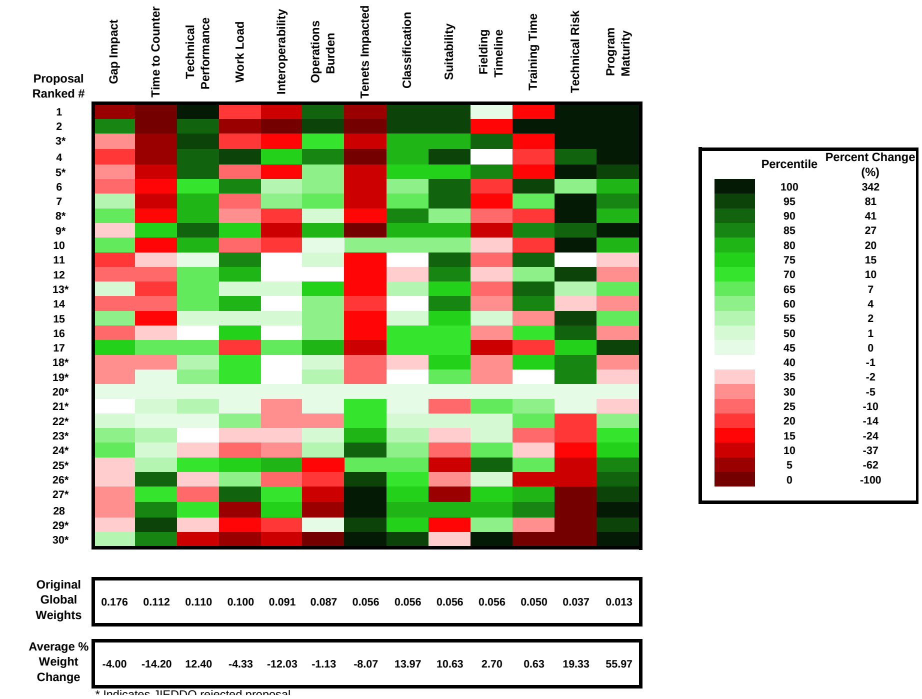

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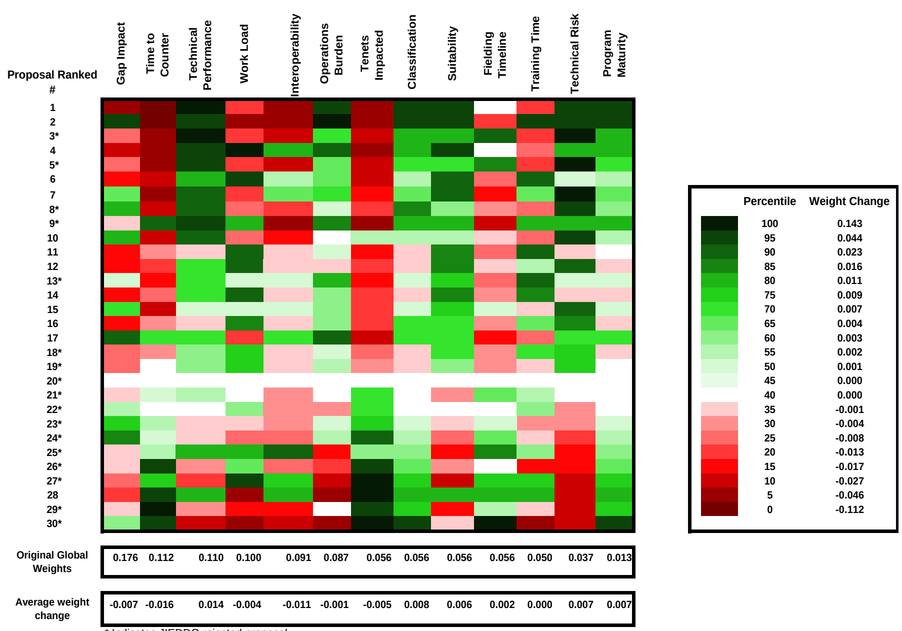

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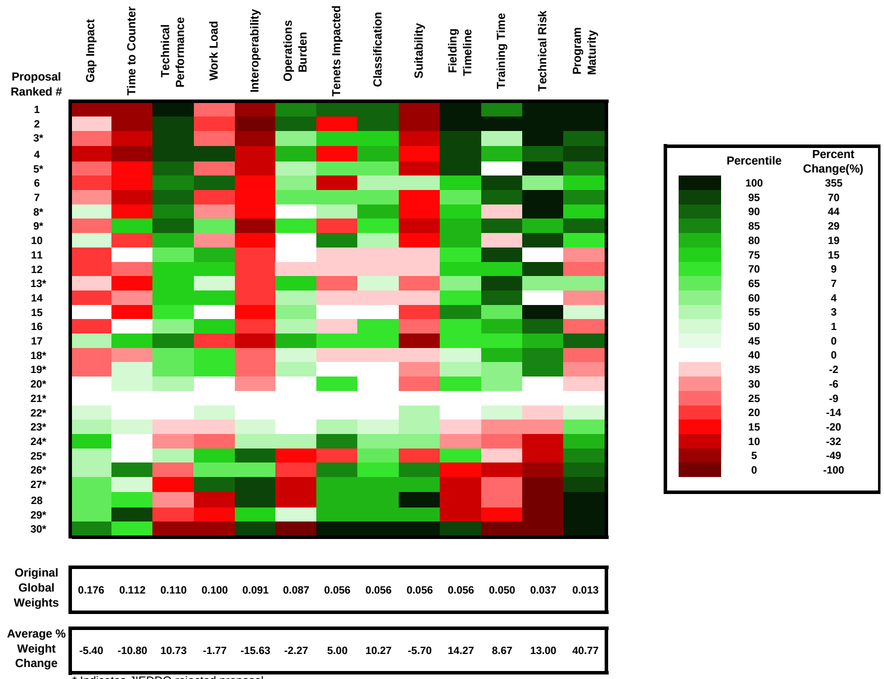

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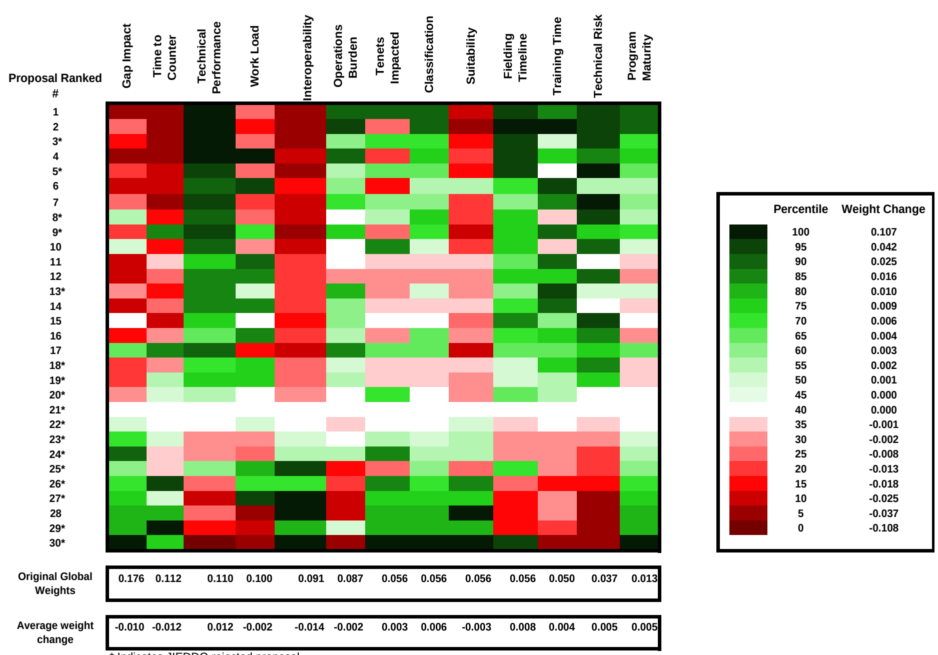

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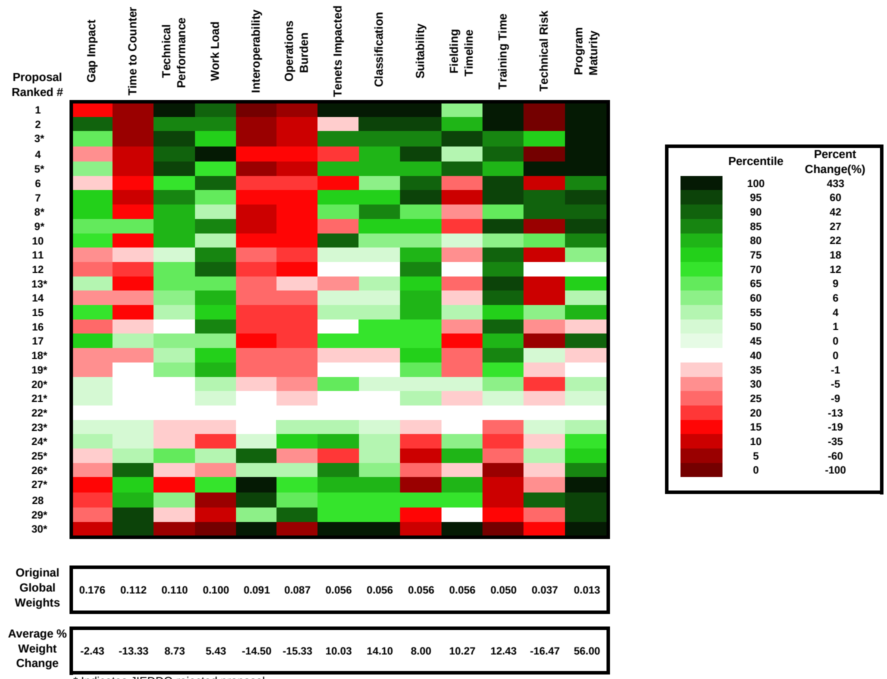

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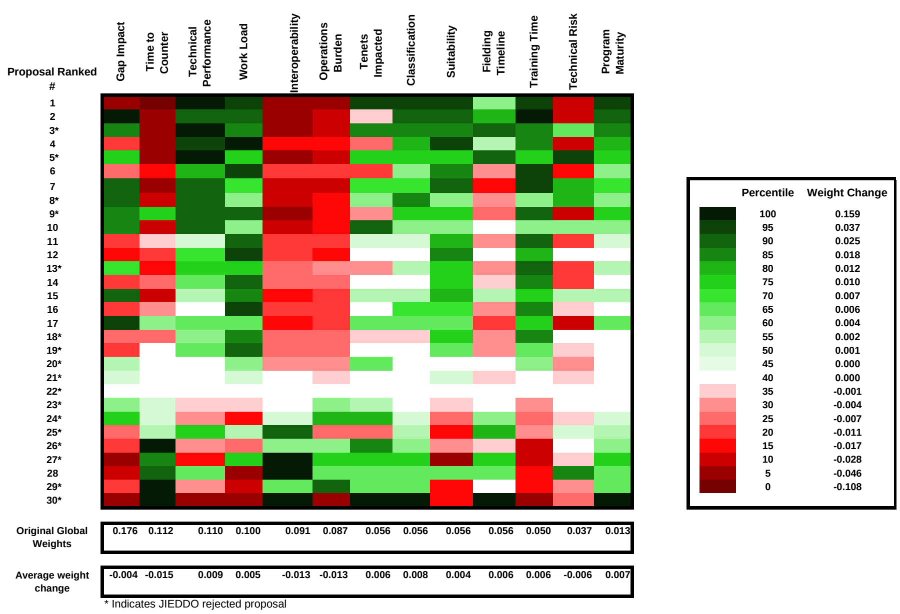

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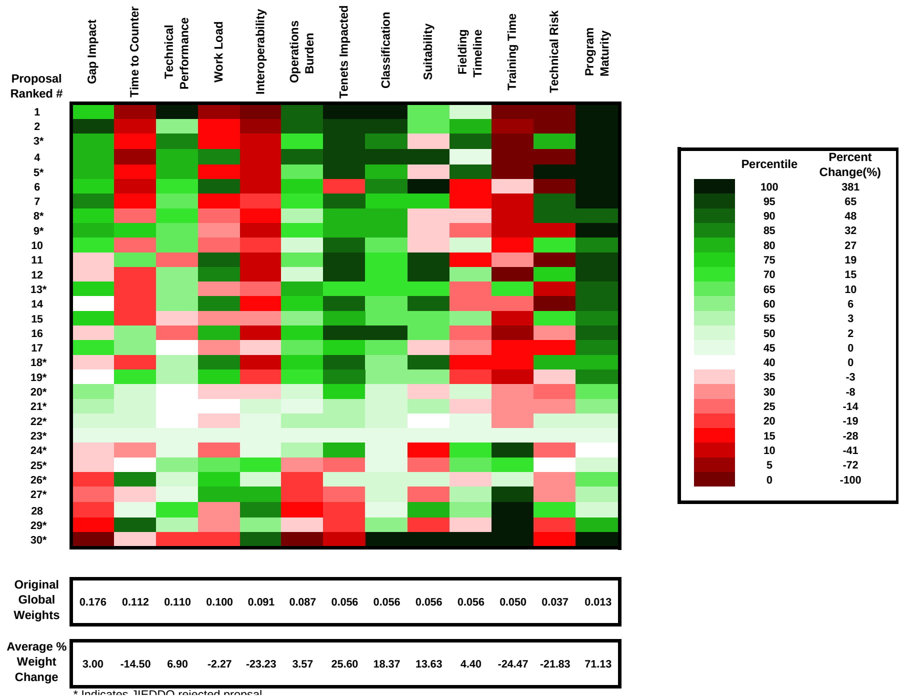

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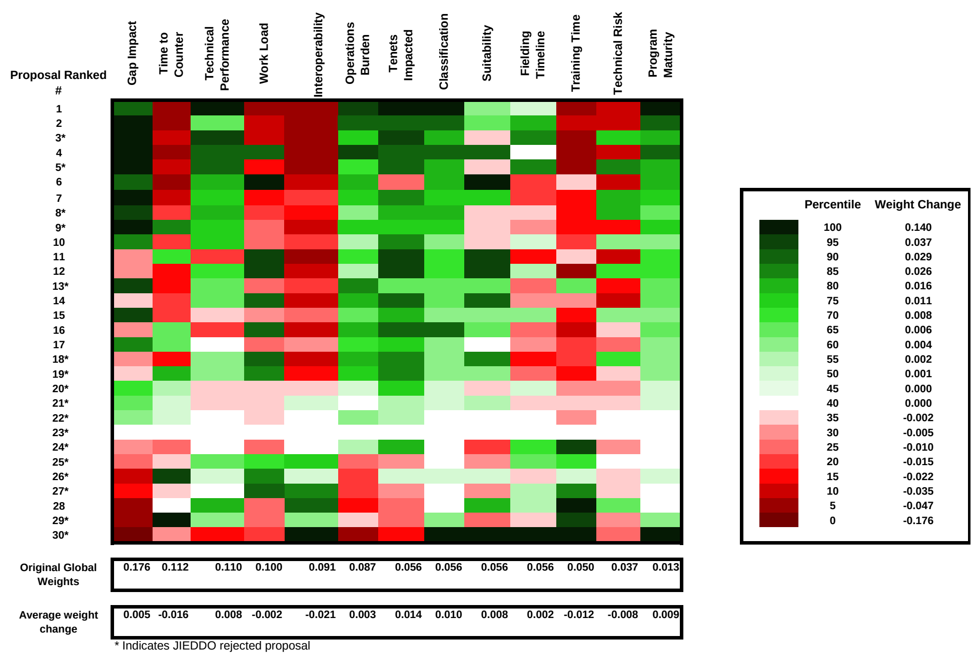

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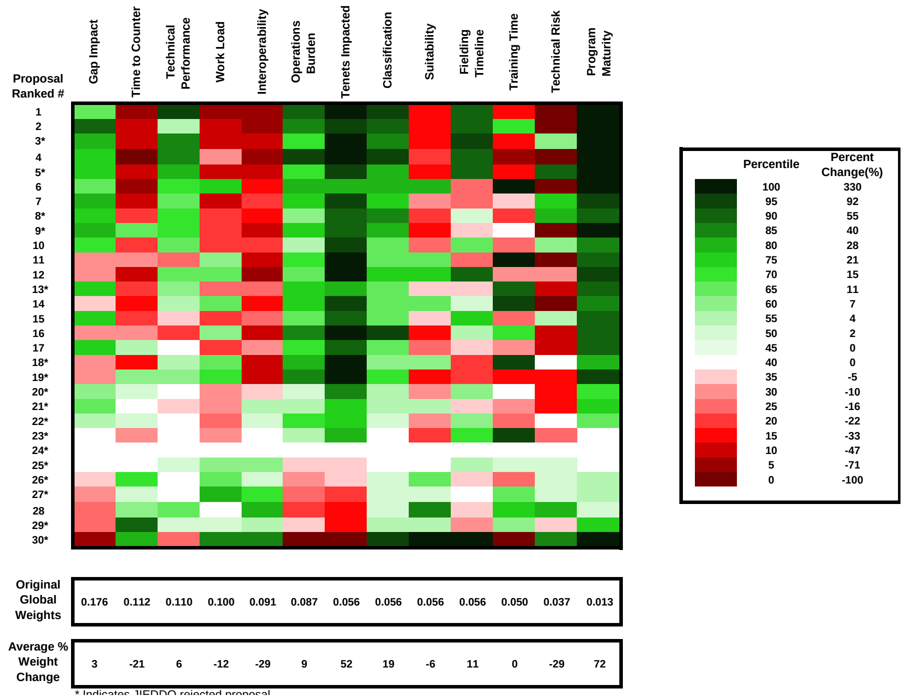

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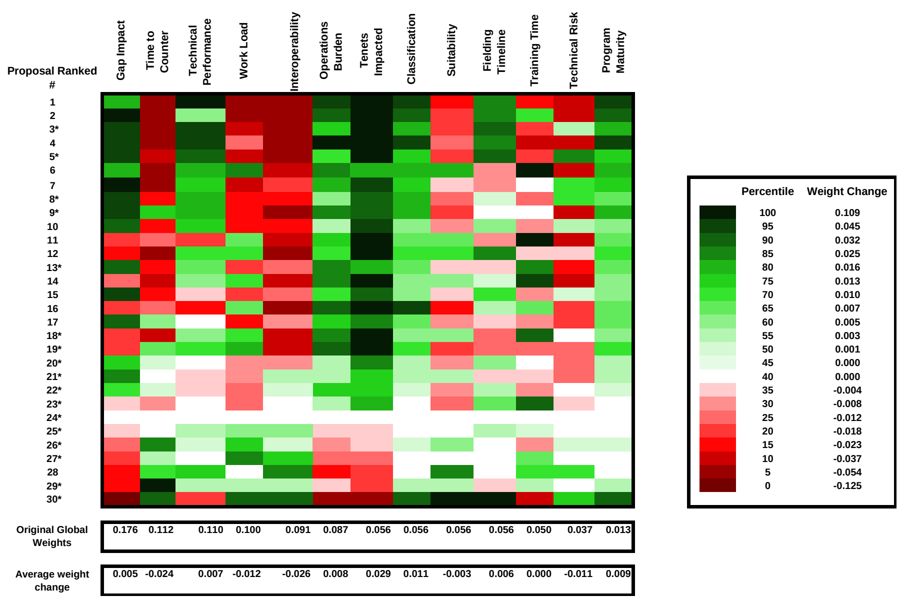

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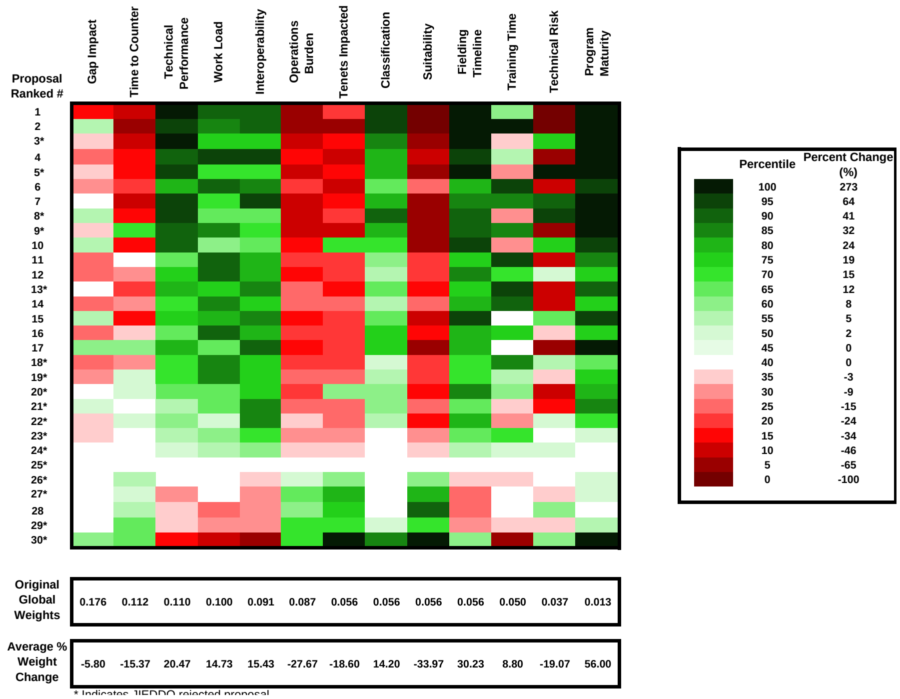

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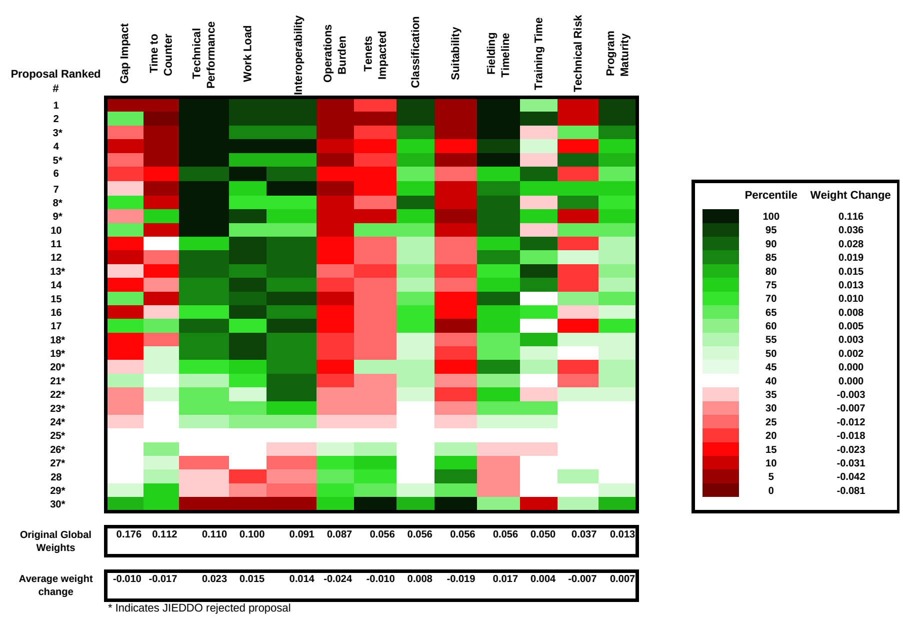

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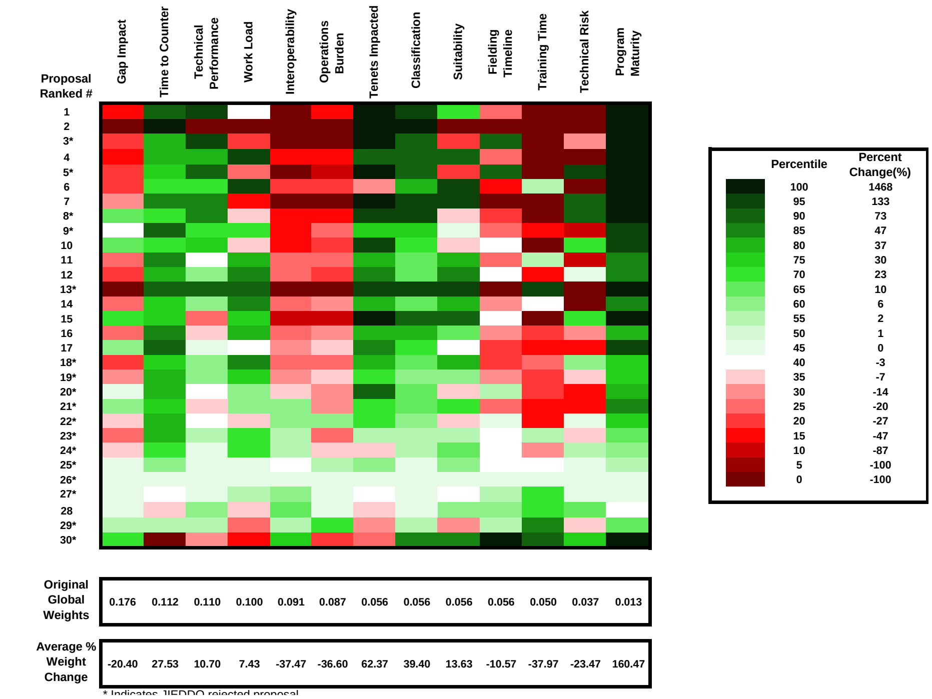

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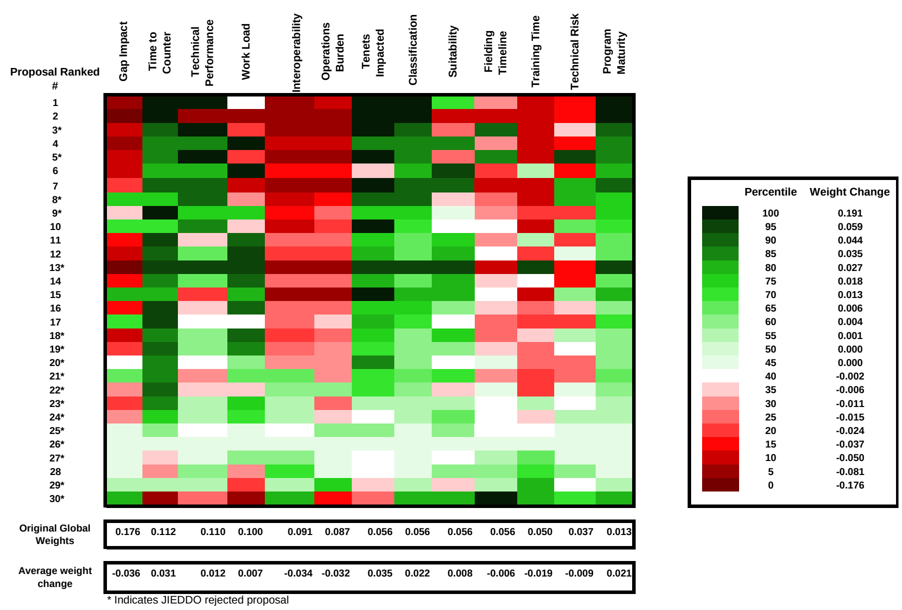

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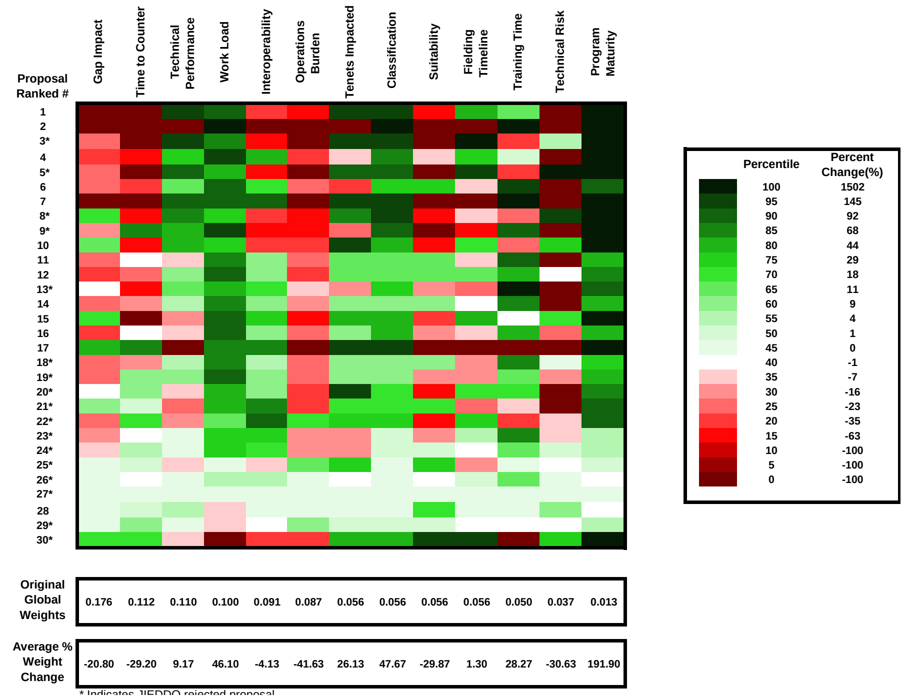

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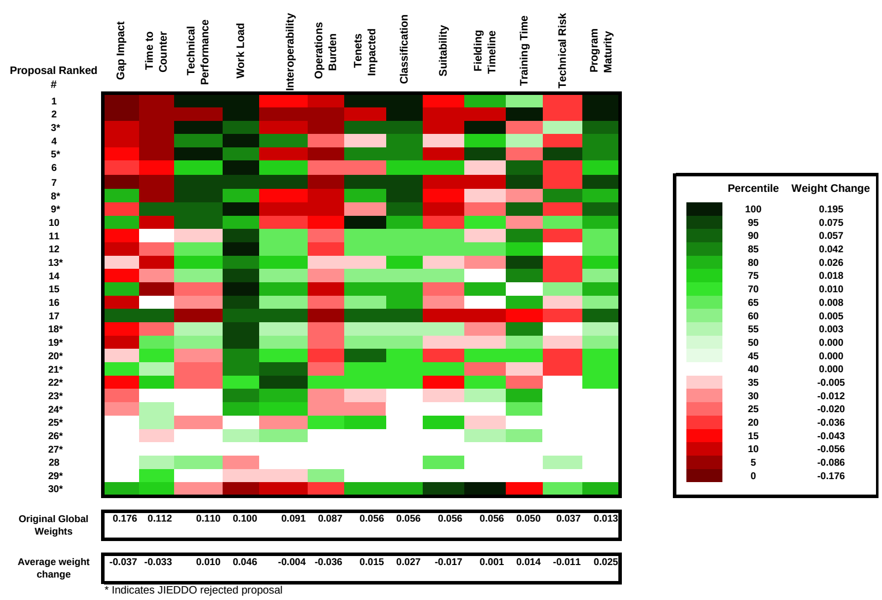

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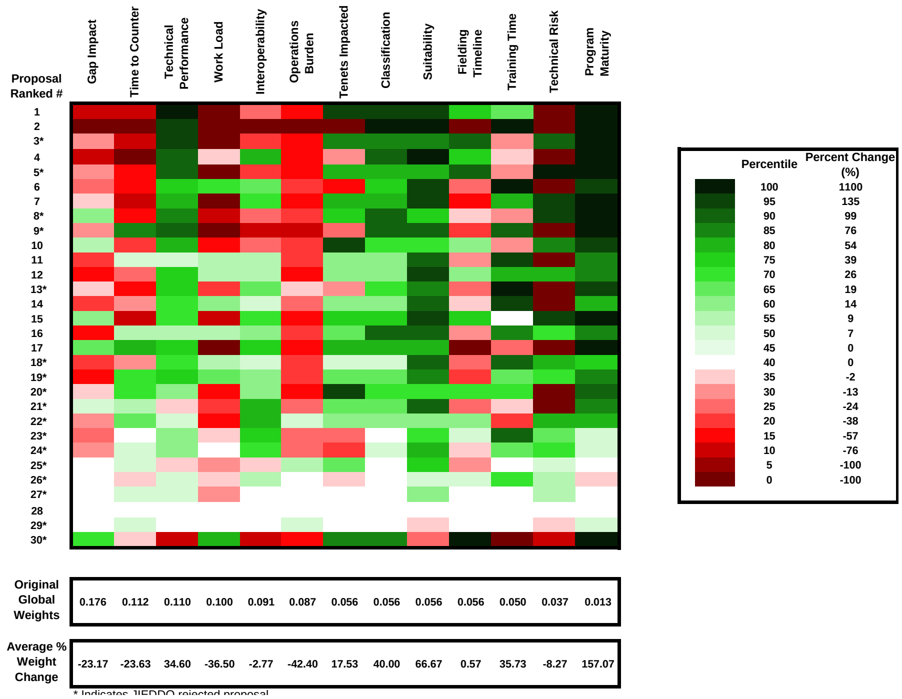

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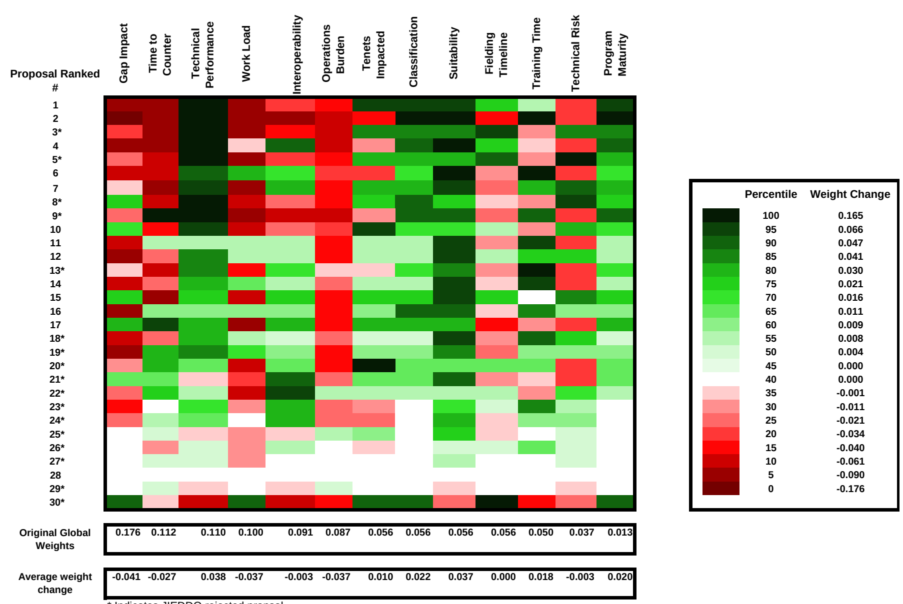

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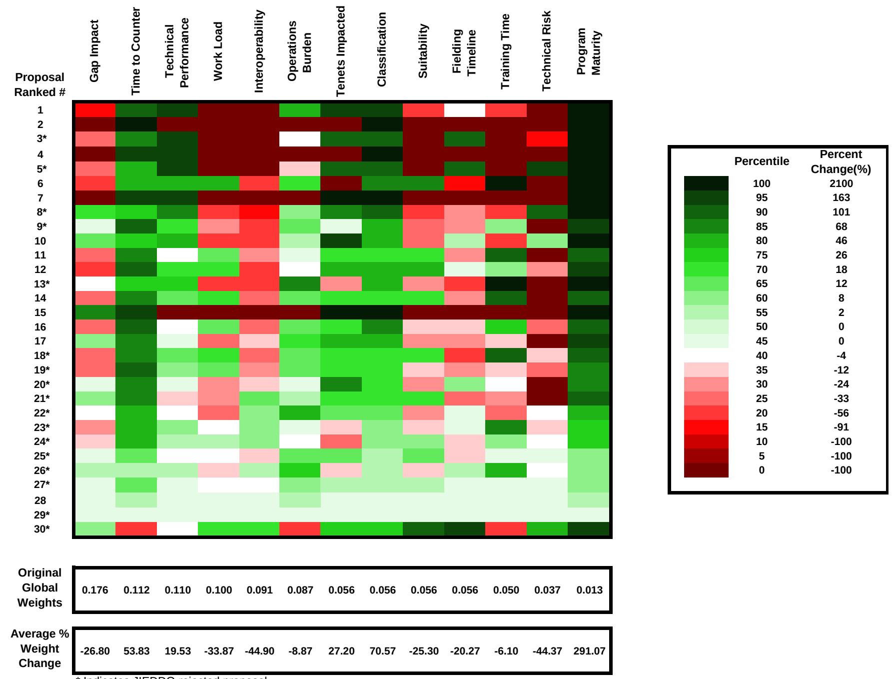

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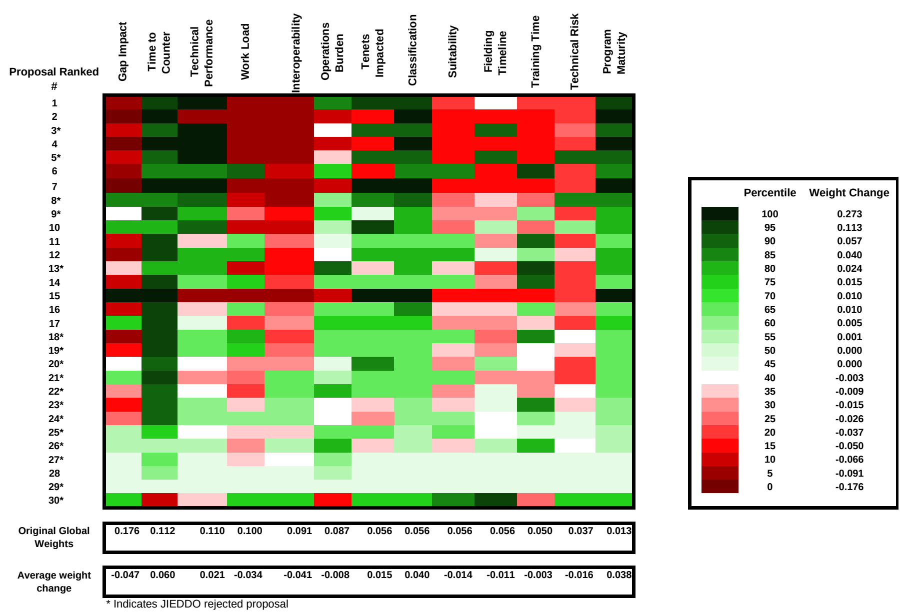

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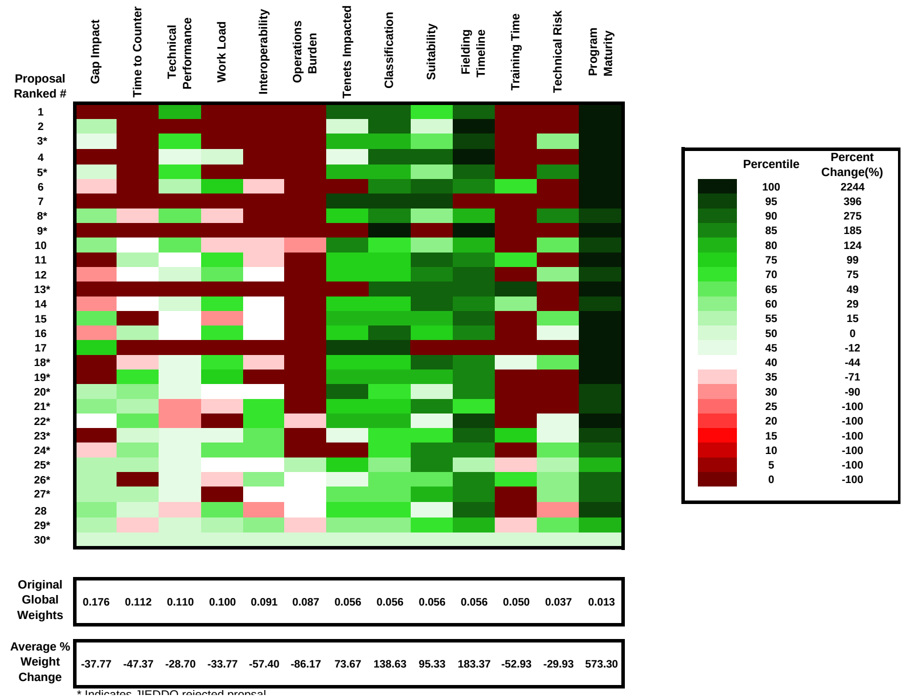

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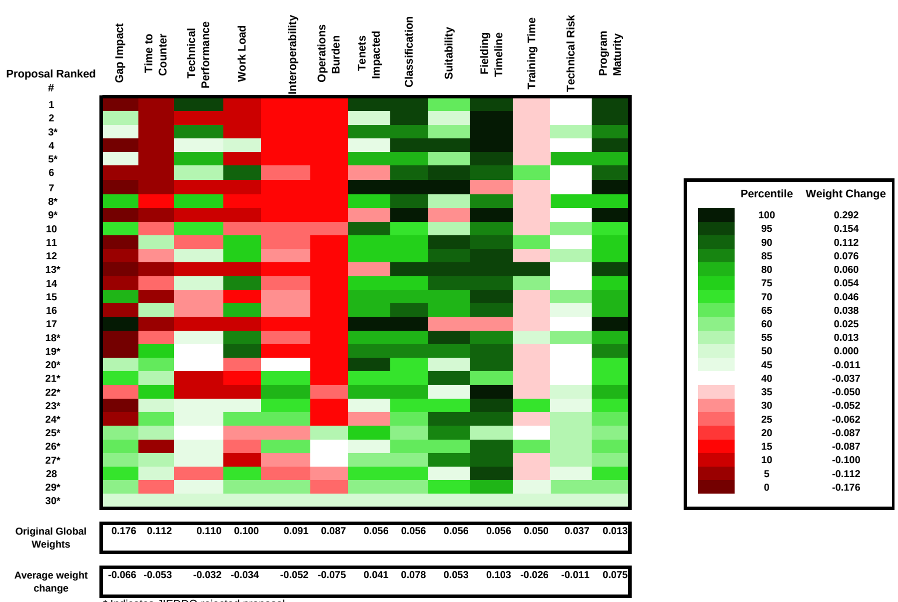

Figure 93: Proposal #30 Weight Change

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Vita

Lt Christina Willy graduated from Central Kitsap High School in Silverdale, Washington in June 2001. Upon graduating, she entered undergraduate degree in mathematics at Barry University in Miami Shores, FL. She entered Air Force Reserve Officer Training program in the fall of her freshman year at the University of Miami. After completing a year and a half of her undergraduate education in Florida, she transferred to the University of Notre Dame. In May of 2005, Christina graduated from Notre Dame and commissioned into the United States Air Force.

In the summer of 2005, Christina moved to San Antonio, TX whereby she was assigned to the Air Force Personnel Center, Randolph AFB, TX. Her primary responsibilities during her first assignment was to oversee the assignment of 1300+ Air Force ROTC cadets into their specialty codes in addition to ensuring that all Air Force 2nd Lieutenants received their appropriate initial skills training and professional military education. In addition to conducting these duties, Christina, was a lead personnel analyst in support of Development Teams whereby she briefed the Air Force's most senior career field managers. Upon graduation from the Air Force Institute of Technology in March of 2009, Christina will move to Washington D.C. to serve in A9 Studies and Analysis Agency.

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 074-0188*

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
26-03-2009	**Master's Thesis**	Jun 2008 - Mar 2009

4. TITLE AND SUBTITLE	
ROBUST SENSITIVITY ANALYSIS FOR THE JOINT IMPROVISED EXPLOSIVE DEVICE DEFEAT ORGANIZATION (JIEDDO) PROPOSAL SELECTION MODEL	**5a. CONTRACT NUMBER**
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	**5d. PROJECT NUMBER** JON 09254
Willy, Christina J., 1st Lieutenant, USAF	**5e. TASK NUMBER** 1.b
	5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S)	**8. PERFORMING ORGANIZATION REPORT NUMBER**
Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/EN) 2950 Hobson Street, Building 642 WPAFB OH 45433-7765	AFIT/GOR/ENS/09-17
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	**10. SPONSOR/MONITOR'S ACRONYM(S)**
Dr. Seth Howell Joint Improvised Explosive Device Defeat Organization (JIEDDO) 2521 South Clark Street Arlington, VA 22202	**11. SPONSOR/MONITOR'S REPORT NUMBER(S)**

12. DISTRIBUTION/AVAILABILITY STATEMENT

APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

Throughout Operations Iraqi Freedom and Enduring Freedom, the Department of Defense (DoD) faced challenges not experienced in our previous military operations. The enemy's unwavering dedication to the use of improvised explosive devices (IEDs) against the coalition forces continues to challenge the day-to-day operations of the current war. The *Joint Improvised Explosive Device Defeat Organization's (JIEDDO)* proposal solicitation process enables military and non-military organizations to request funding for the development of Counter-Improvised Explosive Device (C-IED) projects. Decision Analysis (DA) methodology serves as a tool to assist the decision maker (DM) in making an informed decision. This research applies Value Focused Thinking (VFT), a specific methodology within DA, to the JIEDDO proposal selection process in order to assist DMs in filtering out proposals that do not meet desired C-IED objectives. This research evaluated the validity of the previously developed JIEDDO Proposal Value model to address the following questions: *Does the value model adequately reflect JIEDDO's decision process; and secondly, given the dynamic environment of the current war, how confident can we be in the model's ability to continually and effectively screen proposals based JIEDDO's current values?* The author utilizes multivariate techniques to investigate JIEDDO's ability to make consistent decisions within their proposal evaluation process. Once it has been determined that the model effectively screens proposals, it is possible to proceed with the second question. By consolidating and applying n-way sensitivity analysis techniques the author proposes a consistent sensitivity analysis image profiling technique.

15. SUBJECT TERMS

N-way Sensitivity Analysis, Robust Sensitivity Analysis, Joint Improvised Explosive Device Defeat Organization (JIEDDO), Discriminant Analysis, JIEDDO Value Model, Clustering

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			Kenneth W. Bauer Jr., PhD (ENS)
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